Towards Optimizing the Public Library: Indoor Localization in Semi-Open Spaces and Beyond

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Abstract

We report on the BLIIPS project which aims at the digitalization and optimization of physical, public libraries through the use of artificial intelligence combined with sensor technology. As a first step we introduce FLib, a localization application, and additional developments for interaction with physical books. The contributions of this paper are the introduction of the public library as an interesting testbed for smart technologies, a novel localization application with an experimental evaluation, and a compact research agenda for smart libraries.

1. Introduction

Under names such as the extensible library and library 3.0, the public library is changing (Allison, 2013). In our digital society, a constant stream of innovations and artificially intelligent algorithms turns every possible (physical) interaction in society into data from which algorithms can create value in some way (Zheng et al., 2014). One could assume that public libraries, with their physical books, would become obsolete now information and knowledge rapidly become digital, and huge tech-companies take over. For example, WIKIPEDIA gives us encyclopedial knowledge, GOOGLE BOOKS has many digitalized books, and Mendeley archives bibliographic information.

The future of the library is a much-debated topic which indicates that libraries have always been changing because of new technology in writing, printing, archiving and distributing. More than fifty years ago the visionary J.C.R. Licklider ((1965):33) wrote: "By the year 2000, information and knowledge may be as important as mobility. We are assuming that the average man of that year may make a capital investment in an "intermedium" or console his intellectual Ford or Cadillac comparable to the investment he now makes in an automobile, or that he will rent one from a public utility that handles information processing as Consolidated Edison handles electric power." We can see the modern smartphone or laptop being substituted in this quotation and indeed much of our contemporary information consumption is done through these devices. But despite all electronic access to information, the public library is still the physical place to go to (Palfrey, 2015) for physical books (Baron, 2015) and access to internet, but also things like 21st-century skill building and group activities. Public libraries are innovating in the direction of building communities of interest more or less connected to information: from collection to connection (see also (Palfrey, 2015)).

Here we report on project BLIIPS in which smartphones (and other technologies) are used for an orthogonal purpose: to digitalize physical interactions in the physical library to obtain insight in how physical public libraries are used and how their services can be optimized. In particular we introduce FLib, a localization application which uses machine learning to capture the signal landscape of both WiFi and Bluetooth beacon sensors for localization and navigation in a physical, multi-floor library building. The overall goal of BLIIPS is to optimize the public library, which can be about the layout of the physical space, the content and distribution of the book collection over this space and the visiting patterns of users. The public library is an excellent, semantically-rich, and much underexplored, environment for potential artificial intelligence research such as activity recognition, internet-of-things, optimization (logistics, space, services), and recommender systems.

This paper and contributions are structured as follows. In Section 2 we describe a much underexplored problem domain for artificial intelligence: the physical pub-
lic library. In Section 3 we extensively introduce our FLib localization application based on WiFi and beacon technology. In Section 4 we additionally mention methods for book interaction and conclude with a research agenda for further research in the public library.

2. The BLIIPS project

Companies and governments are looking for ways to utilize their existing data and capture new opportunities to develop initiatives around data. In the Dutch municipality of Alkmaar, such activities are aggregated through so-called triple-helix cooperations in which (local) governments, companies and knowledge institutions collaborate (van Otterlo & Feldberg, 2016). The Alkmaar public library, partially funded by the local government, works together with the Vrije Universiteit Amsterdam on a data-oriented project called BLIIPS (van Otterlo, 2016b). Its goal is to utilize data to optimize the public library in various ways. However, whereas most data-oriented projects are about already digitalized aspects, BLIIPS targets the physical aspects of the public library and seeks to digitalize them with the use of new sensor technology. The overall goal is to gain insight into the physical behavior of patrons (i.e. library “customers”) in the physical library and how to optimize services, for example book borrowing.

2.1. Public libraries: Physical vs. Digital

The main library of Alkmaar is part of the Kennemerwaard group (out of about 150 groups) with 14 locations. Nationwide, in 2014 more than 22 percent of all Dutch people was member of a library, more than 63 million visits were paid to a library, and almost 80 million books were borrowed. However, libraries know very little about their patron’s behavior. In fact, the only behavior visible in data are the books that were checked out. How they use the physical space, how they browse the book collection, which books are being looked at; for this no (real-time) data is available, but could be highly relevant for managing the physical library building, its services and its collection. Libraries do have a long history of measuring, observing and evaluating but typically through labor-intensive surveys and observational studies (see (Edwards, 2009; Allison, 2013; van Otterlo, 2016b) for pointers).

The BLIIPS project represents a first step towards the intelligent library in which this data is collected and analyzed in real time, but also in which the physical environment can provide to patrons “Google-like” services we are accustomed to in the digital world. For example, if all interactions are digitalized, a smartphone could provide location-based, personalized recommendations to physical books in the patron’s surrounding area, based on a user query and data about the library, the patron, and additional sources.

1http://www.debibliotheken.nl/de-branche/stelsel/kengetallen-bibliotheken/

2Related, but used in an orthogonal way, van Otterlo ((2016a)) uses the concept of libraryness as a metaphor to understand modern profiling and experimentation algorithms in the context of privacy and surveillance.
Towards Optimizing the Public Library

2.2. Towards Library Experimentation

BLIIPS builds upon four interlocking developments, see Figure 2a (van Otterlo, 2016b). The first puzzle piece is digitalization: making physical interaction digital through sensors (and algorithms). The second piece connects to retail: the use of smart technology in physical stores, such as the recent Amazon Go Store³. The Alkmaar library has adopted a retail strategy in which the layout and collection, unlike traditional libraries with many bookshelves, are more like a store: lots of visible book covers, tables with intuitive themes and easy categorizations that deviate much from traditional classification systems. A retail view on the problem appeals to customer relations programmes, marketing concepts and so-called customer journeys. The third piece concerns advances in data science, especially developments in machine learning and the availability of tools. The fourth piece of the puzzle, experimentation and optimization, is most important for our long-term goals. The BLIIPS acronym stands for Books and Libraries: Intelligence and Interaction through Puzzle- and Skinnerboxes in which the latter two elements denote physical devices used by psychologists in the last century for behavioral engineering.

The aim of BLIIPS is to influence, or even control, behaviors and processes in the library in order to optimize particular goals, such as increasing the number of book checkouts. Such digital Skinnerboxes are becoming a real possibility due to the combined effect of data, algorithms and the ubiquity of digital interactions (van Otterlo, 2014). The library though, is a perfect environment for experimentation, unlike many other domains. As Palfrey (2015, p213) (quoting Kari Lamsa) writes: “Libraries are not so serious places. We should not be too afraid of mistakes. We are not hospitals. We cannot kill people here. We can make mistakes and nobody will die. We can try and test and try and test all the time.”

3. An Indoor Localization Application

Mapping patron activity in the physical library requires at least knowing where they are. For this, we describe design and implementation of the FLib application. Localization is a well-studied problem (Shang et al., 2015; He & Chan, 2015), but the practical details of the environment, hardware and algorithms used can deliver varying results and so far, localization is not solved (Lymberopoulos et al., 2015). First we outline requirements and then we describe an interactive localization application (Warnaar, 2017).

3.1. Indoor Localization

Whereas for outdoor localization GPS is successful, indoor localization remains a challenge. GPS works by maintaining line of sight to satellites which is problematic inside concrete buildings. Several indoor positioning systems exist (Shang et al., 2015; He & Chan, 2015) none of which is currently considered as the standard. Sensor information such as magnetic field strength, received radio waves, and inertial information from gyroscopes and odometers can be used to determine location. Smartphones are equipped with an array of sensors; they are well suited as indoor positioning devices. Lymberopoulos et al. (2015) review the 2014 Microsoft indoor localization competition (featuring 24 academic teams): “all systems exhibited large accuracy variations across different evaluation points which raises concerns about the stability/reliability of current indoor location technol-

³https://www.amazon.com/b?node=16008589011

⁴Typically average errors of a couple of meters.
gies.” Indoor spaces are often more complicated in terms of topology and spatial constraints: wireless signals suffer from multipath effect, scattering, and a non-line of sight propagation time, thereby reducing the localization accuracy. Due to the small scale, most applications require better accuracy than outdoors.

3.2. Library: Requirements and Solutions

Our target is the library of Alkmaar\(^5\), a medium-sized city in the Netherlands. Its properties and the overarching BLIIPS project induce requirements for localization. First, the library consists of two floors (see Figures 1a and 5a) with mainly semi-open space. Unlike several room-based approaches, the library hardly contains constraints such as rooms/corridors. In terms of localization accuracy, we require (topical) area-based accuracy for effective navigation to library sections, and more accurate when technically feasible. Second, we want to leverage existing infrastructure as much as possible. Third, our solution needs to be amenable to incremental accuracy improvement without having to repeat all deployment steps. Fourth, obtained data in the deployment step should be reusable. Fifth, computational complexity should be low enough on smartphones. Sixth, smartphones should aid in obtaining required measurements for deployment. And last, the application needs to engage the user by visually showing the location and the patrons surroundings (or provide navigation in a later stage).

A common base of many solutions is fingerprinting: measuring the signal landscape such that localization amounts to matching currently sensed signals with the landscape. Shang et al. (2015) distinguish five main elements of a localization solution: (1) **Sensors and hardware.** Localization depends on the interplay between sensor technology and devices such as smartphones. Sensors include wireless modules (e.g. WiFi, Bluetooth) and motion sensors (e.g. accelerometers, gyroscopes). Other well-known hardware are Zigbee and RFID chips. (2) **Measurements.** Localization depends on what is being measured from sensors. Most techniques use received signal strength (RSS) of a sensor. Derived measures such as distances and angles towards sensors are typically employed for triangulation approaches similar to GPS. An ideal signal should have two properties: recognizability and stability. (3) **Spatial contexts.** To aid localization, techniques such as map matching, spatial models (of behavior, but also of topological room connection structures) and landmarks can be used. These can be used in the localization process or as a top-level localization decision by employing the spatial context as a constraint. (4) **Bayesian filters.** Probabilistic approaches are effective for dealing with uncertainty in measurements. The most general formulation of Bayesian localization comes from Bayes’ rule: \( P(x|o) = \frac{P(o|x)P(x)}{P(o)} \) in which \( x \) is the location and \( o \) a set of measurements (the observation). A sequence of observations \( o_1, o_2, \ldots, o_n \) is used to infer the sequence of locations \( x_1, x_2, \ldots, x_n \), assuming there are (meaningful) (in)dependencies in the observations and locations. Such assumptions give rise to various probabilistic models that can be used for localization from noisy observations such as (extended) Kalman filters and hidden Markov models. All models have a bias wrt. choice of distributions used for e.g. sensor models \( P(o|x) \) and how to do inference and learning. In prior experiments we employed a particular Monte Carlo based probabilistic model for localization, the particle filter, in our VU environment (see Figure 2b). A particle filter keeps multiple hypotheses (particles) of the location. Each time a patron moves, the particles are (probabilistically) moved based on a motion model to predict the next location. After sensing particles are resampled based on recursive Bayesian estimation using a sensor model that correlates the sensed data with the predicted state. Eventually the particles will converge on the true position. We concluded that obtaining accurate motion and sensor models was not feasible in this stage. A second bottleneck was the computational complexity on the phone when even a moderate number of particles and iterations were used. (5) **Hybrid localization.** A combination of techniques can improve the accuracy. These include multimodal fingerprinting, triangulation fusing multiple measurements, methods combining wireless positioning with pedestrian dead reckoning, and cooperative localization.

\(^5\)http://alkmaar.bibliotheekkennemerwaard.nl/
Each localization technique has drawbacks when considering accuracy, cost, coverage, and complexity. None of them can be suitable to all scenarios. Based on our requirements formulated above we choose a (multimodal) fingerprinting solution in which we use smartphones both for measuring the signal space and for patron localization. Fingerprinting is accurate enough for our purpose, does not pose any assumptions on knowledge about where signals come from nor on the modeling of the domain (e.g., sensor models), and can be employed using the existing WiFi infrastructure which we extend with Bluetooth beacons. Other requirements (like low computational complexity and local computation) are fulfilled by the choice of (simple) algorithms with few biases and interactive visualizations on the phone, and because fingerprinting supports reuse of data. We use simple topological graphs and grid-based decompositions of space tailored to the required localization precision.

3.3. Localization by Fingerprinting

Localization by fingerprinting is a widely employed technique (He & Chan, 2015). The general principle is depicted in Figure 1b. Each black dot is a reference point: a location in the space from which all received signals together form a fingerprint. In the picture two received signal sets are depicted for two different reference points. More formally, let $R$ be the set of reference points and $A$ be the set of APs. We denote a sensed signal with strength $s$ from AP $a \in A$ as the tuple $(a, s)$. Now, let $f = \{(a_1, s_2), (a_2, s_2), \ldots, (a_n, s_n)\}$ be the set of all signals sensed at a particular location, called a fingerprint over the set $A$. A reference point can denote a point $(x, y)$ in space (rendering $R$ infinite), but usually is taken from a finite set of regions, grid locations (see Figure 5a) or nodes of an abstract topological graph such as in Figure 1a. A fingerprint database $F_{DB}$ is a set of pairs $(r, f)$ where $r \in R$ is a reference point and $f$ a fingerprint over the set $A$.

In the Offline training phase we first collect data. Here a reference point $r$ is (physically) visited to measure the signals available $(f)$ at that location and to store $(r, f)$ in the database. To increase the accuracy of $F_{DB}$, multiple fingerprints can be taken at the same location. Systematically all reference points $r \in R$ should be visited. When building prediction models the fingerprint database $F_{DB}$ is used to obtain a generalizable mapping $M : 2^A \times R \rightarrow R$, i.e., a mapping from a set of signals (and their signal strengths) to a reference point in $R$. All samples $(r, f) \in F_{DB}$ represent a supervised learning problem from fingerprints (inputs) to reference points (outputs). In the Online localization phase. $M$ is used for localization. Let the to-be-located-patron be in some unknown location $l$ in the space, and let the set of current signals be $c = \{(a_1, s_2), (a_2, s_2), \ldots, (a_n, s_n)\}$. The predicted location of $l$ is then $r = M(c)$.

The choice for fingerprinting naturally induces a supervised machine learning setting in which the signal landscape over the space is the desired function to learn, and where the fingerprints are samples of that function. Intuitively, this determines the balance between $|R|$ and sample complexity (Wen et al., 2015). Fingerprinting is not prone to error drift such as often seen when using inertial sensors to determine step count and direction. Modelling signal decay over distance and through objects is also not required, as is the case for multilateration positioning. Another advantage is that the positions of APs do not need to be mapped. Disadvantages are that collecting fingerprints of the site is a tedious task (Shang et al., 2015) and that changes to the environment may require that (some) fingerprints need to be collected again.
3.4. Multimodal Fingerprinting: Beacons

One of the constraints is that the library building has only 8 different WiFi APs. Several other APs from surrounding buildings can be used but they are outside our control and less reliable. In contrast, our test VU environment (see Figure 2b) has many APs inside. To enrich the signal landscape, we employ so-called Bluetooth low energy (BLE) beacons. A beacon is a self-powered, small device that sends out a signal with a adjustable signal strength and frequency. Beacons are a recent addition to the internet-of-things landscape (Ng & Wakenshaw, 2016) and most modern smartphones can detect them. For example, a museum can place a beacon at an art piece and when the visitor gets near the beacon, his smartphone can detect this and provide information about the object. Most work employs beacons for areas such as rooms and corridors (i.e. region-based). For example, LoCo (Cooper et al., 2016) is a fingerprinting system based on WiFi APs and BLE beacons which are mostly aligned with the room-like structure of an office. Such beacons act as noisy indicators for rooms. Such constraints are somewhat present in our VU environment, but not at the library. In a sub-project (Bulgaru, 2016) we tested region-based interpretations in the library with varying success due to the noisy nature of beacons.

Here, in our semi-open library space we opt for a more general approach; to employ beacons as extra signals for fingerprinting and to treat them similar to WiFi signals. Beacons are configured such that signals will be received throughout large portions of the library, just like the (much stronger) WiFi APs. Using this approach roughly 10 beacons per floor are effective. Consequently, in our model, the set $A$ of all APs is extended with all beacons $\{b_1, \ldots, b_n\}$.

3.5. The FLib Localization Application

In this section we describe FLib, a smartphone application for localization purposes in a real-world environment. Figure 4b shows an overview of main (software) components of FLib. In subsequent sections we will review all parts. FLib is targeted at our testing ground at the university (see Figure 2b) and the library in Alkmaar (see Figures 1a and 5a).

3.5.1. Fingerprinting

The fingerprint database $F_{DB}$ is filled by smartphone measurements, see Figure 3. In FLib the current position can be selected on an interactive map, after which the fingerprint is generated with a single button tap. Initial experiments in VU and LIBRARY employed a graph-like transition structure as in Figure 1a which was replaced by a more uniform grid layout as depicted in Figures 4a and 5a. When the user fingerprints a grid location, it gets highlighted to keep track of visited areas. The Estimate Android SDK is used to collect Bluetooth signals. WiFi RSSIs are collected using Android’s BroadcastReceivers. The Estimote software uses an adaptable scanning period and a pause between scanning periods. If the first is too short, few or no beacons are detected, but if it is too long location-estimation lags behind (and: huge performance differences between smartphones exist).

3.5.2. Fingerprints Server

Measured fingerprints are uploaded to a server application, (implemented in PHP using Symfony running on Apache, using a MySQL database). Fingerprints are first locally stored on the phone and then sent to the server. The server’s only function is to store fingerprints data: localization runs locally on the phone.

3.5.3. Model Training

The data on the server $F_{DB}$ is used for building a model mapping fingerprints to grid locations (reference points). We utilize two different machine learning algorithms: $k$-nearest-neighbors ($k$-NN) and multi-layer perceptrons (MLP), see (Flach, 2012).

The first model is a lazy learner; generalization and model building is not required, but instead $F_{DB}$ is loaded on the smartphone and the algorithm finds the $k$ most similar fingerprints in $F_{DB}$ for the currently sensed signals. We use a modified Euclidean distance to compute a similarity metric between fingerprints. Given a fingerprint $f = \{(a_1^f, s_1^f), \ldots, (a_m^f, s_m^f)\} \in F_{DB}$ and the currently sensed signals, $c = \{(a_1^c, s_1^c), \ldots, (a_m^c, s_m^c)\}$, we compute the distance between $c$ and $f$. Let $A^{lc} \subseteq A$ be access points measured in both $c$ and $f$. We compute distance $d(c,f)$ as follows. For all sensed APs in $A^{lc}$ we take the overall Euclidean distance between signal values. A penalty of 30 is added to the distance for each access point $a \in A$ that is only in $f$ and not in $c$, or only in $c$ and not in $f$. This empirically estimated value balances signals and missing values.

Our second model is an MLP, a standard neural network with one hidden layer of neurons, an input layer with $|A|$ neurons and an output layer with $|R|$ neurons. Reference points are taken as classes and each class ($r \in R$) is represented by a separate neuron. For the input layer we transform a sensed fingerprint $\{(a_1^s, s_1^s), \ldots, (a_m^s, s_m^s)\}$ with $m \leq |A|$ to a vector of length $|A|$ where each $a \in A$ has a fixed index in this vector and each value at that index is the sensed signal
strength \( s_i (i \in 1 \ldots m) \). All other components of the input vector are 0. To construct an output vector for a fingerprint \( f \) (i.e. \((r, f) \in F_{DB}\)) we use a binary vector of length \(|R|\) with all zeros except at the index of the neuron representing \( r \). Training an MLP amounts to computing the best set of weights in the network which can be accomplished using gradient-descent learning.

### 3.5.4. Real-time Localisation

Both models can be used to generate a ranking \((r_1, \ldots, r_m)\) of all reference points. k-NN naturally induces a ranking based on distances. MLPs however, yield a normalized distribution over the output nodes. Instead of showing only the best prediction of location, FLib shows a more gradual visualization which highlights with shades of blue where the patron may be. To render the blue tiles as in Figure 5b, we calculate the transparency for the returned unique reference points. Let \( R_{best} = \langle r_1, r_2, \ldots, r_n \rangle \) be the ranked locations where some \( r \in R \) can occur multiple times. The first element gets score \(|R_{best}|\), the second \(|R_{best}| - 1\) and so on, and scores for the same \( r \) are summed. Scores are normalized and mapped onto 50…255, inducing color value as a shade of blue.

### 3.6. Experiments and Outcomes

Experiments were conducted at two separate locations: part of the 5th floor of the main building at the VU university in the A-wing (vu) and the two publicly accessible floors at the Kennemerwaard Library at Alkmaar (library). The library ground floor is 55 m wide by 22 m in length, while the first floor is 54 m wide by 40 m in length. The vu testing floor is 57.4 m wide and 20.5 m in length. Estimote Proximity and BeaconInside beacons were both used. Transmission rate and power were (497ms, −16dBm) and (500ms, −3dBm) for Estimote and BeaconInside beacons respectively. Fingerprinting was done with different smartphones: OnePlus A3003 (3), LG H320 (Leon), and Huawei Y360-U61 (Y3). All access points in the vicinity are used for fingerprints collection to increase WiFi signal space. For vu, we have 396 unique AP addresses in the fingerprints collection, compared to 165 for library. A Bluetooth scanning period of 2500 ms was used to balance delay and detection. RapidMiner was used to train MLPs (learning rate 0.3, momentum 0.2, normalized inputs) and inference in models runs on the phone.

#### 3.6.1. Experimental Setup

First, we determine whether unlabelled walked trajectories can successfully be classified at vu. We use the graph model from Figure 2b and fill \( F_{DB} \) with fingerprints taken at each node position. Next, we walk several trajectories such as shown in Figure 6a, and store unlabelled fingerprints of multiple locations. Using 1-NN with the modified Euclidean function, the predicted sequences of reference points are compared to the truly walked paths.

Positioning performance over the grid at vu and library (Figures 4a and 5a) is calculated by taking the mean hamming distance \( \bar{H} \) between \( n \) true \((x, y) \in R\) and predicted reference points \((x', y') \in R\):

\[
\bar{H}(M) = \frac{1}{n} \sum_{i=1}^{n} |x_i - x'_i| + |y_i - y'_i|
\]

Fingerprints are collected with different phones, while fingerprints of walks were collected with a OnePlus 3
only. Differences in performance are compared using only fingerprints of OnePlus3, averaged fingerprints, and all fingerprints. Best performance is expected when using fingerprints from the same phone as for the walks, since there are no sensor or configuration differences. In all fingerprints for the ground floor at Library, 745 records were collected, and 623 for the first floor. Averaging fingerprints data per phone per reference point was done to decrease computational complexity of $k$-NN, reducing $|f_{DB}|$ for the first floor from 623 to just 72. Computational efficiency is important because smartphones have limited battery time, and positioning delay is reduced.

3.6.2. Results

First, we look at 2 VU walk example results:

| True $W_1$ | {5A-00b, 5A-55x, 5A-71x, 5A-00d, 5A-99, 5A-00e, 5A-88, 5A-00g, 5A-72, 5A-56, 5A-PA, 5A-00b} |
| True $W_2$ | {5A-00b, 5A-55x, 5A-71x, 5A-00d, 5A-99, 5A-00e, 5A-00g, 5A-72, 5A-56, 5A-PA, 5A-00b} |
| Predicted $W_1$ | {5A-00b, 5A-55x, 5A-71x, 5A-00d, 5A-99, 5A-00e, 5A-88, 5A-00g, 5A-72, 5A-56, 5A-00b} |
| Predicted $W_2$ | {5A-00b, 5A-00e, 5A-55x, 5A-71x, 5A-00d, 5A-99, 5A-00e, 5A-00g, 5A-72, 5A-56, 5A-00b} |

We see that predicted and true sequences are very similar, with the exception of some natural additional predicted neighboring locations. For VU, the positioning performance for our MLP and $k$-NN configurations are displayed in Figure 7a. In the best case, 2-NN, we have an average hamming distance error of 2.67 (1.65 in $x$ and 1.02 in $y$). Each grid tile is 2.05 m in width and length, so we roughly (under)estimate the mean error with $\sqrt{(1.65 + 2.05)^2 + (1.02 + 2.05)^2} \approx 3.97$ m.

For Library, the accuracy of different configurations over averaged fingerprints (ground floor) is in Figure 7b. Figure 7c shows results for the first floor. Ground floor tiles cover 5.5 x 4 m. For the Library ground floor the best result (MLP, 50 hidden, 200 cycles) is a mean total hamming distance of 1.06: 0.65 for $x$ and 0.41 for $y$ and roughly (under)estimated error of $\sqrt{(5.5 \times 0.65)^2 + (4 \times 0.41)^2} \approx 3.92$ m. For the Library first floor, the same configuration yields the best result: 0.80, with an error $x = 0.35$ and $y = 0.45$. Each grid tile covers 6.75 x 8 m, giving an (under)estimated mean error of $\sqrt{(6.75 \times 0.35)^2 + (8 \times 0.45)^2} \approx 4.30$ m. These levels of indoor localization performance suffice to detect a patron’s region at Library, and can be used for several future applications. We have seen that using $k > 3$, positioning performance starts degrading, so only results of $\{1, 2, 3\}$-NN are reported.

3.7. Related Work

There is much related work in localization, e.g. (He & Chan, 2015; Shang et al., 2015; Lymberopoulos et al., 2015). Our major contribution is the library domain and its potential for library optimization; in terms of pure localization accuracy several systems may be better. However, the BLIPS project’s requirements on accuracy are less strong for the tasks we aim at. A relatively novel aspect is that we aim at semi-open spaces and do make different use of multimodal (i.e. with additional beacons) fingerprinting than in other systems such as (Cooper et al., 2016; Kriz et al., 2016). Direct comparison of empirical results is for this reason not feasible. In the past only very few such systems have been considered for (public) library settings (see (van Otterlo, 2016b) for pointers) and the results were very limited; here our contribution lies in a successful mix of previously known techniques in a library setting.
4. Elements of a Research Agenda

The BLIIPS project has a main goal: to establish a library experimentation facility to experiment with ways to optimize the public library services by influencing patrons, for example by interacting with patrons through recommendations or by changing the layout of the library or its collection. The FLIB application represents a large step towards turning patron behaviors into actionable data. We envision many other challenges and opportunities for the intelligent library and briefly mention some directions.

(1) Fingerprinting/localization. Current efforts go into extending and upgrading FLIB to increase accuracy and to incorporate more spatial context and other (semantic) constraints coming from the library. Other types of (deep) machine learning and especially (structured) probabilistic models are appealing. In addition, we want to investigate i) collaborative fingerprinting (using many devices), and ii) the optimization of the choice for, and placement of, sensors in the environment (e.g. (Shimosaka et al., 2016)).

(2) Digitalization. In addition to our use of WiFi and beacons, a sub-project in BLIIPS targeted interaction with physical books (Jica, 2016), with computer vision and using RFID chips contained in each book (see Figure 8 for an example). Books can be looked up based on i) cover, ii) bar code, iii) RFID chip, iv) textual information (ISBN). Combined with localization (movement) data, this further completes the digitalization of library activity. However, we envision more ways to digitalize physical processes, using various new types of sensors, developments in networks (e.g. LoraWAN), existing technologies such as "smart shelves", augmented/virtual reality, and more.

(3) Activity recognition. More detailed data of digitalized, physical activities can be distilled and used for predictive models. Traditional library research has analyzed data before, but the scale of current and potential behavioral data is virtually unlimited and many interesting challenges await: can predictions be made who will do which activity, for how long, and with what purpose? A general big data frame can connect such data with demographics, geographical context, weather, trends on social media, and much more.

(4) The personalized library In line with BLIIPS’s philosophy of making the physical library more Google-like, personalization will be a big issue in the data-driven public library. Knowledge classification schemes, recommendations, advertisements and suggestions for activities could all be personalized based on data (e.g. books borrowed) combined with statistical predictions derived from many patrons. The physical setting enables location-based interventions such as personalized suggestions about interesting books in the local neighborhood.

(5) Optimizing all services. Prediction models can enable optimization of processes by means of experimentation. For example, one can systematically change aspects of the library services using expectations and actually see the results in the data. Optimization requires goals. Potential library optimization goals that are largely unexplored are i) the number of books people borrow, ii) distribution of (types of) books in the collection, iii) the most efficient layout of the library, and iv) the conceptual arrangement of knowledge (classification schemes). One advantage of data-oriented approaches is that monitoring...
and intervening can be done in real time. The advantage of sensor technology is that at some point one can relax the physical order of the library because, for example, books can be located individually, escaping the standard order of the shelf. Coming up with the right goals – together with the right hardware and algorithmic technology – that are aligned with the many functions of the public library, is most challenging. (6)

**Privacy.** More data means more risks for privacy in general. Libraries already collect data about their patrons, but this will increase quickly. Challenges are basic data privacy and security. However, a more hidden form is intellectual privacy (see (van Otterlo, 2016a)). Personalized interventions in library services based on information about borrowing history can have transformative effects on the autonomy of a patron in thinking and deciding. Consequences of data-driven strategies in libraries are underexplored (but see (van Otterlo, 2016b)) and need more study.

5. Conclusions

In this paper we have introduced the public library as an interesting domain for innovation with artificial intelligence. In the context of project BLIIPS we have introduced the FLib localization application as a first step towards patron activity monitoring, and have briefly touched upon additional results related to book interaction. Many potential future work directions on BLIIPS and FLib exist and were outlined in the research agenda in the previous section.

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References


