Human Assisted Positioning Using Textual Signs

Bo Han* Feng Qian* Moo-Ryong Ra*
AT&T Labs – Research, Bedminster, New Jersey, USA
{bohan,fengqian,mra}@research.att.com

ABSTRACT

Location information is one of the key enablers to context-aware systems and applications for mobile devices. However, most existing location sensing techniques do not work or will be significantly slowed down without infrastructure support, which limits their applicability in several cases. In this paper, we propose a localization system that works for both indoor and outdoor environments in a completely *offline* manner. Our system leverages human users' perception of nearby textual signs, without using GPS, Wi-Fi, cellular, and Internet. It enables several important use cases, such as offline localization on wearable devices. Based on real data collected from Google Street View and OpenStreetMap, we examine the feasibility of our approach. The preliminary result was encouraging. Our system was able to achieve higher than 90% accuracy with only 4 iterations even when the speech recognition accuracy is 70%, requiring very small storage space, and consuming 44% less instantaneous power compared to GPS.

1. INTRODUCTION

Location is one of the key context information and has enabled numerous context-aware systems and applications. To determine the location, today's mobile devices use various sensors and related techniques such as GPS, Wi-Fi fingerprinting, cellular triangulation *etc.* All these approaches let the device figure out the location automatically and each of them complements one another by having distinct characteristics of availability, accuracy, infrastructure requirements, and resource consumption. However, most existing techniques rely upon the infrastructure support and/or heavy training for their proper use. For instance, on many smartphones, A-GPS (Assisted GPS) is typically used to get an initial location fix quickly. In this case, nearby cell towers or equipment directly connected to towers originate and deliver hints to smartphones so they can narrow down the search space. Without the help, it will take a long time to bootstrap the localization system. Some other localization techniques also require heavy training on the region of interest. Radio signal based fingerprinting techniques, such as ultrasound, Wi-Fi, and FM radio are representative examples.

In this paper, we propose an alternative positioning system by leveraging a human's perception of her surroundings. The location is computed based on what the user sees and tells the system. One notable difference from prior art is that the acquisition of location information can be performed based on only local information. This is particularly useful for wearable devices. As depicted in Table 1, many such devices, including Google Glass and Apple Watch, do not have GPS, thereby the only way for them to obtain location information is to ask their paired devices, typically a smartphone. Moreover, the capability of completely local computation enables several unique use cases, which are articulated in §2.

Device name	Release	Has GPS	Has Cellular	Has Wi-Fi
Google Glass	2013/03	No*	No	Yes
Samsung Gear 2	2014/04	No	No	No
Apple Watch	2015	No	No	Partial**

* The sensor might exist but not yet accessible through the API.
** Can only communicate with its paired phone.

Table 1: Localization sensors on popular wearable devices.

Figure 1: Examples of textual Signs in outdoor environment.

Our localization methodology leverages *textual signs* we see every day. They include street signs, local business logos, public transportation signs, house numbers, decorative logos, *etc.* These textual signs offer several properties making them ideal as location signatures. First, they are prevalent as long as the area is reasonably populated (§5.1). Second, they are easily recognizable and readable with little ambiguity. Third, users can easily identify those spatially and temporally stable signs (Figure 1) and ignore those temporary signs that are not suitable for fingerprinting the location, such as text on a vehicle or on an advertisement banner. In contrast, automated approaches such as Optical Character Recognition (OCR) may have difficulties detecting many texts due to their diverse styles (examples in Figure 1), and OCR cannot tell which signs are stable. Another benefit of using text is the resultant signature database is small in size. As shown in Table 2, each entry corresponding to a sign takes only a few bytes. Therefore, the database of a large regional area can be stored locally. By integrating the database with offline maps, the entire positioning system can run locally without requiring GPS or Internet connectivity. The database can be constructed and updated by crowdsourcing without any domain knowledge or specialized equipment (*e.g.,* by leveraging Google Street View, see §4), making it much easier than collecting data for traditional maps [17]. For positioning, the user can, for example, read out several (*e.g.,* 3 to 5) signs nearby she sees. The text is recog-

*All authors made equal contribution.

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ID	Text	Location	Tag
1	Greene St.	40.729256,-73.995753	Road
2	West 4 St.	40.729256,-73.995753	Road
3	Rocco Restaurant	40.727938,-74.000157	Restaurant
4	23 St. Station	40.745528,-73.998623	Transportation
5	Downtown Brooklyn		(subway)
6	Century 21 dept. store	40.774097,-73.982095	Shopping
7	Imagine	40.775921,-73.975867	Landmark
8	Regal	40.757065,-73.989077	Cinema
9	405	40.774135,-73.950709	House number

Table 2: Sign database for signs in Figure 1.

nized and then matched against the database to localize the user. Out scheme works in both outdoor and indoor environments.

In this paper, we make the following contributions. First, we collect real data from Google Street View and OpenStreetMap [5] and examine the feasibility of our idea. Second, we design robust algorithms to tolerate various inaccuracies and ambiguities due to human perception, the user input procedure, and the signs themselves (§3), and then perform a simulation study to demonstrate the feasibility of the proposed algorithm (§5.2). Third, in our system's regime, users can use different means to enter the text of the signs. Among others, we conducted a case study using speech recognition, which is convenient for wearable devices such as Google Glass and the result was very encouraging (§5.3). Unlike general-purpose natural language interfaces [1], our speech recognition module uses a simple language model and usually a small vocabulary consisting of words on nearby signs. Thus, the entire processing chain is able to run locally.

Note that, our goal is to build a human-assisted positioning system that achieves outdoor and indoor localization in a complete offline manner without using GPS, Wi-Fi, cellular, and Internet connectivity. We do not expect our approach to replace traditional localization methods. Instead, it provides a very useful alternative when traditional approaches cannot work due to various reasons.

2. MOTIVATION: USE CASES

We motivate our approach by discussing several use cases.

"Offline" Localization. Bob's grandmother is visiting him. Realizing she was lost in the unfamiliar city, she called her grandson. Using our system, Bob is able to quickly figure out where she is by asking her to describe her surroundings. In some cases, the same goal can be achieved by checking the street signs. However, street signs are not always nearby and not always available (*e.g.,* in a theme park or shopping mall).

Facilitating Location Search and Recollection. Alice barely remembers the place where she met her friend last week. It was near a Starbucks and a Thai restaurant. Our system provides a way to effectively search this location based on the limited information.

Offline Localization on Wearable Devices. Many wearable devices such as Google Glass and Apple Watch do not have GPS (Table 1). Consequently, the only way for them to obtain location information is to ask their paired smartphones via Bluetooth. Therefore, if the user does not bring her smartphone, or if the phone runs out of battery, the wearable device cannot know its location. Our proposal fills this gap by requiring neither location sensor (GPS, Wi-Fi, cellular, *etc.*) nor Internet connectivity. It works in both outdoor and indoor environments.

Infrastructure-free Indoor Localization. Localization in indoor environments usually requires hardware beacons and/or heavy training. In our approach, location can be determined by leveraging existing textual signs such as room names and numbers. The sign database can be easily constructed by walking in the building and/or marking the locations of textual signs on the floor map.

3. LOCALIZATION SYSTEM DESIGN

Our proposed system consists of three components: the sign database, the user input module, and the localization algorithm. When a user enters a nearby textual sign, it is matched against the sign database to get a set of candidate locations. These locations then are fed into the localization algorithm to refine the user's location. The above steps are repeated until the user's actual location is pinpointed. We detail the three components below.

Challenges. At first glance, the proposed scheme looks straightforward. One key challenge, however, is to handle the inaccuracy that may appear in each step. First, the user may misread some signs. Second, the user may only enter part of the sign based on common conventions. For example, "King Harbor Seafood Restaurant" can be partly entered as "King Harbor" or "King Harbor Seafood". Third, the user input module (*e.g.,* the speech recognition engine) may make mistakes by translating the text to something different. Fourth, the same sign (*e.g.,* "Bank of America") may appear in multiple places thus causing ambiguities. Last but not least, a sign recognized by the user may not be in the database. We need robust algorithms to tolerate such inaccuracies. Another challenge stems from the fact that our system runs completely locally on mobile devices with limited storage, computation capability, and battery life. Therefore, it needs to be as lightweight as possible to minimize the resource consumption, but without compromising the accuracy and user experience.

3.1 The Sign Database

The sign database contains precise locations of the textual signs. It can optionally contain tags for other value-added services. Based on the original database, our system generates an auxiliary data structure called *token table* by splitting each textual sign into separate words (*i.e.,* tokens) and constructing mappings from each token to the set of signs in which the token appears. For example, from Table 2, we have "rocco"→{3}, and "regal"→{8} where "rocco" and "regal" are two tokens, and the numbers are sign IDs. The reason for introducing tokens is to tolerate errors. As will be described in §3.2, user input is processed at the basis of each token instead of each sign as a whole. Therefore, if the user only enters part of a sign, or if there are mistakes in some words of the sign, the sign may still be identified because some tokens partially match.

3.2 User Input Interface

Our system can accommodate any input interface as long as the method let users conveniently enter the tokens. For instance, speech recognition can be used. Or if an on-screen keyboard is available, one can simply type. We mainly focus on speech recognition (SR) as our primary input interface because microphone is one of the most prevalent sensor on mobile devices and SR is particularly suitable for wearable devices. When the user reads out a nearby sign, the SR engine translates her speech back into the text, which is then processed by the localization algorithm. SR performs a series of computations to find a match between a raw voice signal with words (or sentences) in the database. Typical SR processing chain requires three models: an acoustic model, a phonetic dictionary, and a language model. The acoustic model translates continuous raw voice signal to *phones*. The phonetic dictionary enables to map the *phones* to words [1]. The language model decides legitimate sentences *e.g.,* word A cannot appear after word B.

In our initial design, we keep our language model simple in order to make the size of local database for SR as small as possible. As a result, the user input is recognized at the basis of each word token. Our SR is thus unaware of the structure of the text on signs as it only

[1]"words" and "tokens" are interchangeable in this paper.

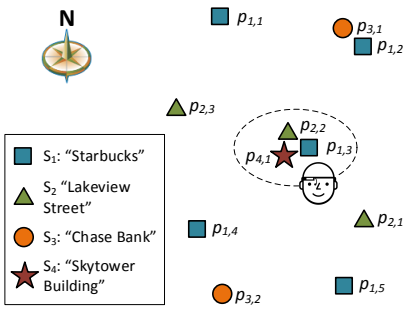


Figure 2: An example for illustrating the localization algorithm.

translates user's speech into individual tokens. Here is the high-level description of token recognition procedure. Let the input be a sequence of tokens $\{t_i\}$. Their matched signs $\{s_i\}$ can be quickly identified by looking up each t_i in the token table (§3.1). A token can match zero, one, or more signs in the token table. For each token t_i, we define its *frequency* $f(t_i)$ as the number of its unique matches (*i.e.,* signs containing t_i) divided by the total number of unique signs in the database. Tokens with high $f(t_i)$ are ignored based on a predefined threshold (*e.g.,* 0.001 based on Figure 4) because they are unlikely to have enough discrimination power.

Also, note that the phonetic dictionary and language model can be changed dynamically in our case. Specifically, in the incremental update phase (§3.3), it only contains a small subset of all tokens in the database depending on where the user is. These operations can be done locally on most mobile devices, given the fact that nowadays it is common to observe multi-core CPUs on mobile platform and we have a relatively small number of tokens *e.g.,* several thousand per city (§5.3). All those factors discussed so far *i.e.,* simple language model and dynamically generated model files, contribute to reduce the complexity of the SR engine, thereby making it feasible to run on today's mobile devices with reasonable accuracy, as to be demonstrated in §5.3.

We admit that, as a completely offline approach, our SR accuracy can be potentially inferior to those cloud-based SR systems backed by large database. Also, tokens with same or similar pronunciations make it inherently difficult to distinguish them. To mitigate this issue, we also includes a feature allowing a user to correct the SR result at a *per-token* basis. The system displays its best guess, as well as k other candidate tokens and a "not listed" option so that the user can correct the result within a time window by using either voice command or physical buttons.

3.3 The Localization Algorithm

The localization algorithm works in a continuous manner. It takes as input a stream of signs $S = \{s_i\}$. The output is either the estimated location or *unknown* indicating the location cannot be accurately determined due to a lack of input.

For each s_i, we find its entries $p_{i,j} (1 \leq j \leq k_i)$ in the database where k_i is the number of entries of s_i in the database. Assume we have m signs s_1,...,s_m from the user. Some signs might be incorrect. Also some may correspond to multiple locations (*i.e.,* $k_i > 1$). In order to automatically filter out incorrect signs and locations, we leverage a key assumption that the majority of signs should have (at least) one entry appearing near the user's true location because the user can see them. That is to say, for at least m_0 signs, $\exists j'$ such that $p_{i,j'}$ is close to the true location, assuming we get $m_0 \leq m$ signs correct. Consider an example in Figure 2. The user enters four signs s_1, s_2, s_4, and something else that is mistakenly interpreted into s_3 (*e.g.,* due to inaccurate speech recognition). s_1, s_2, and s_3 appear at multiple locations in the database. Despite of these noises, $p_{1,3}$, $p_{2,2}$, and $p_{4,1}$ form the largest cluster, which with high probability corresponds to the user's real location.

Algorithm 1 Localization Algorithm

```
1: S = {s_i}, t = 2, stop = FALSE;
2: while (stop <> TRUE && t <= T) do
3:    found = 0;
4:    for (∀S' ⊆ S, |S'| = t) do
5:       r = centroid of S';
6:       if (∀s_i, s_j ∈ S', distance(s_i, s_j) < D ) then
7:          found++;
8:       end if
9:    end for
10:   t++;
11:   if (found == 0) then
12:      stop = TRUE; Output: unknown location;
13:   else if (found == 1) then
14:      stop = TRUE; Output: location is r;
15:   end if
16: end while
17: if (found <> 1) then
18:    Output: unknown location;
19: end if
```

Following the intuition from Figure 2, we design a localization algorithm, with the high-level idea of searching for the largest cluster of signs by gradually increasing the size of the set of correct sign locations. As shown in Algorithm 1, For any subset of 2 possible locations, we measure their distance and count the number of subsets with distance smaller than D, a pre-defined threshold. If we do not find any such subset, the location is unknown. If such subset if unique, the estimated location is the centroid of this subset of locations. If there are multiple such subsets, we repeat the above procedure for any subset of 3 possible locations, 4 possible locations,... until the subset size reaches a threshold $T \leq |S|$. We empirically found this algorithm is more robust than off-the-shelf clustering algorithms such as k-means for our problem. We evaluate its accuracy in §5.2.

Bootstrapping and incremental update are two scenarios in which the above algorithm can be applied. In the bootstrapping phase (*e.g.,* when the device is turned on), our system has no knowledge of the user's previous location. In this case, the search space in the sign database can be large (*e.g.,* at city level). Afterwards, in the incremental update phase, the system can use the user's last known location (if it is "fresh" enough) to predict the user's current coarse-grained location, which can be leveraged to significantly reduce the textual sign search space. This leads to higher accuracy for both speech recognition (as the vocabulary becomes smaller) and the localization algorithm (because a sign corresponds to fewer locations). One way to estimate the user's coarse-grained location is as follows. Let (x_0, y_0) be the user's previous location measured ΔT minutes ago. Let V and D be her maximum walking speed and her range of visibility, respectively. Assuming the user only walks, then the location of signs she currently sees, denoted as (x, y), must satisfy $(x - x_0)^2 + (y - y_0)^2 \leq (V\Delta T + D)^2$. Clearly this is the most simple and conservative estimation, which can be significantly improved by considering walking speed [11], direction [23], and other coarse-grained localization techniques by leveraging various sensors. The bootstrapping phase will be triggered manually or automatically, for example, after sensing the user has taken a vehicle or a train [12]. We demonstrate the benefits of incremental update in §5.

3.4 Discussions

In this subsection, we discuss some limitations of our system and potential user interface suitable to our system.

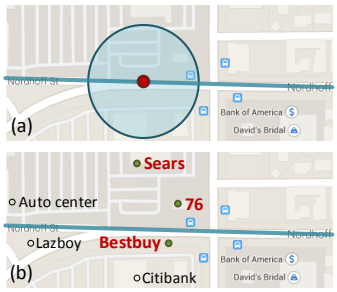


Figure 3: (a) Traditional GPS-based map. The thick blue line is the computed route. (b) Map using sign-based localization. Entered signs are highlighted. Some other signs not yet entered are also displayed to help user identify them, and enter them by selection or speech.

Comparison to Fully-Automated Approach. An inherent limitation of our approach is the localization usually takes longer, and it is difficult to derive a bound for the accuracy, because we rely on human users instead of location sensors. Therefore, our system will *not* replace automated localization methods. Instead, it provides a useful alternative when traditional approaches cannot work due to various reasons (*e.g.,* in use cases described in §2). Notably, our proposal does have one crucial advantage: by asking users to actively participate in the localization process, it can improve users' space awareness and their recollection of the environment [10].

Map User Interface. In traditional GPS-based mobile maps, the app directly shows user's location, as shown in Figure 3(a). However, our approach uses neither the distance nor the direction information of the signs so it is difficult to leverage triangulation to pinpoint the user's exact location. Instead, we propose to directly highlight the textual signs entered by the user so that she can (probably more easily) figure out her location by using the signs as references. The display is updated when the user enters the next token. Between consecutive updates, the map can move slowly based on user's walking speed and direction, in order to make the location update smoother. Signs not yet entered can also be displayed (but not highlighted) to help user identify them, and enter them by simply selecting (or reading) them. This makes sign-based navigation very convenient, as shown in Figure 3(b).

Comparison to Offline Maps. Several vendors (*e.g.,* Garmin and Baidu) provide offline maps allowing users to access them without Internet connectivity. However, users still need to use GPS or Wi-Fi fingerprinting to locate themselves on the map. Our work attempts to bridge this gap by making localization completely offline. Also, Baidu Map [2] provides a "search in view" feature allowing users to search POI (Point of Interest) names within the currently displayed area. But it only searches for one POI (*e.g.,* KFC) at a time and shows all its instances, making it not suitable for localization.

Using General Landmarks. Potentially, the landmarks can be extended from textual signs to more general objects (*e.g.,* a particular statue on a street). However, compared to textual signs, these general landmarks provide much more vague description of the location, and using them as location signatures may cause more ambiguities. We will consider this direction in future work.

4. DATA COLLECTION

To demonstrate the feasibility of our proposal, we collected data from two sources: Google street view and OpenStreetMap [5].

Google street view is a feature in Google Maps that provides panoramic views from positions along many streets in the world. We randomly picked 19 outdoor locations in the U.S., Canada, U.K., and two indoor locations. For the AT&T Building, we conducted a real walk

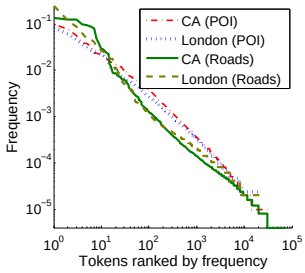


Figure 4: Ranked token frequency (both axes in log scale).

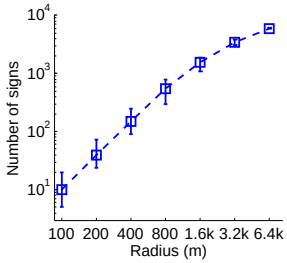


Figure 5: Number of signs within a confined area (London).

and collected the signs. For all other 20 locations, we randomly select spots with street view, "walk" in the street for a short distance ($\sim$ 0.1 mile), and manually record observed textual signs. The results are shown in Table 3. The street view approach allows us to construct high-quality signature database without physically going to the site, and is ideal for crowdsourcing. For example, an interface can be easily added for users to tag the signs in street view images. Some sign images can also be used as CAPTCHAs so that all Internet users can contribute. We do notice a limitation of using street view images from one single repository: some signs are blocked by obstacles so Table 3 only reports a subset of signs.

OpenStreetMap (OSM). We also crawled OSM to obtain names of POI (point of interest) in much larger areas. OSM [5] is a crowdsourcing-based world mapping project involving 200,000 contributors in 2011 [17]. The OSM raw data [6] employs three main data structures to represent map elements: node, way, and area. We built a custom tool that analyzes these data structures and extracts their associated names (if they exist). We assume each POI has a sign corresponding to its name on the map. For a *node*, the sign's location is the same as the node's. For an *area*, we pick a random node on its boundary as the sign's location. For *ways*, we extracted their names but the road signs' locations are difficult to estimate. One limitation of this synthetic approach is that it only produces a subset of signs whose contents and locations may also deviate from those of the real ones. However, we believe the dataset is sufficient for our feasibility study in §5, in which we study three areas: London metropolitan area (55K signs), New York City ($\sim$21K signs), and the state of California (139K signs).

5. PRELIMINARY RESULTS

Using the two data sources described in §4, we show preliminary results to demonstrate the feasibility of our proposal.

5.1 Characterizing Textual Signs

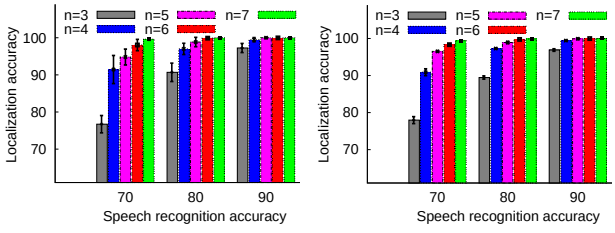
Sign Popularity. Table 3 summarizes the Google street view results. For the vast majority of the 21 locations covering diverse environments, we observed a non-trivial amount of textual signs. Generally, the signs are denser in downtown than in suburb and residential areas. However, we did not find a strong correlation between sign density and city size (except for very large cities). In indoor environments, signs mostly consist of room names and numbers. We believe our system is applicable in most places. Note that obviously temporary signs (*e.g.,* ad banners) and signs that are too general (*e.g.,* traffic signs) are not included in Table 3.

Token Distribution. Next, we characterize tokens in two locations: the state of California and the London metropolitan area. For each location, we examine tokens in POI signs and tokens in road signs, from OSM. This results in four token sets. Figure 4 shows log-log plot of the ranked frequencies of the four sets. The distributions are heavy-tailed. Although a tiny fraction of tokens, which will be ignored by the localization algorithm, are very general, the vast

Table 3: Signs collected from Google street view.

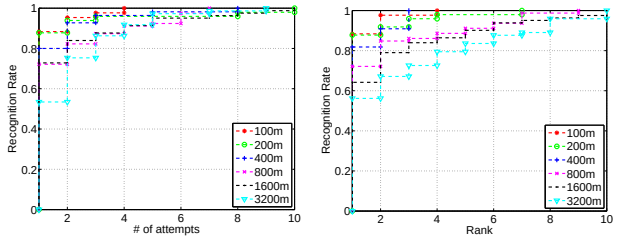
Location Type	City Name	City Population	Approximate Location	Walked Dist.	Num of Signs
Big city, downtown	New York City, NY	8.4 M*	9th Ave. / 54th St.	0.1 mile	24
Big city, residential	Queens, NY	2.2 M	37th Dr. / 108th St.	0.1 mile	12
Big city, downtown	Chicago, IL	2.7 M	State St. / Madison St.	0.1 mile	15
Big city, suburb, residential	Oak Park, IL**	51 K	S East Ave. / Randolph St.	0.2 miles	8
Big city, suburb, residential	Portland, OR	584 K	SE Mill St. / SE 11th Ave.	0.1 mile	11
Big city, suburb	St. Louis, MO	318 K	S Broadway / Stansbury St.	0.2 miles	11
Mid-sized city, downtown	Chattanooga, TN	173 K	E 8th St. / Market St.	0.1 mile	11
Mid-sized city, downtown	Salinas, CA	164 K	E Gabilan St. / Monterey St.	0.1 mile	11
Mid-sized city, suburb	Loveland, CO	70 K	N Lincoln Ave. / E 29th St.	0.1 mile	9
Mid-sized city, suburb	Aberdeen, SD	26 K	S 5th St. / SW 12th Ave.	0.2 miles	9
Mid-sized city, suburb	Fairbanks, AK	32 K	N Cushman St. / 1st Ave.	0.1 mile	9
Mid-sized city, suburb, residential	Prince Albert, SK, Canada	35 K	Bennett Dr. / 4th Ave. West	0.2 miles	12
Small city, tourism	Key West, FL	25 K	Southard St. /Duval St.	0.1 mile	22
Small city	Riverton, WY	11 K	E Park Ave. / N Broadway Ave.	0.2 miles	10
Small town, residential	Fairfield, IA	9 K	E Adams Ave. / S Main St.	0.2 miles	8
Small town	Rushville, IL	3 K	S Congress St. / W Lafayette St.	0.1 mile	13
Small town	Windermere, Cumbria, UK	8 K	Near town centre	0.1 mile	9
University campus	Ann Arbor, MI		U of Michigan north campus	0.1 mile	6
Theme park	San Diego, CA		The Seaworld theme park	0.1 mile	6
Indoor, museum	Chicago, IL		Art Institute of Chicago	0.1 mile	10+
Indoor, office building	Bedminster, NJ		AT&T Building ***	0.1 mile	10+

Notes: * Includes all five boroughs of New York City. ** Near Chicago. *** Our office building. Conducted real walk.



(a) NYC (b) London

Figure 6: The accuracy of localization algorithm.



(a) Accuracy with # of Attempts. (b) Rank Distribution.

Figure 7: SR performance: The results are potentially the worst case since the participant was a non-native speaker and we use the Sphinx software out-of-box, *i.e.,* without optimizing acoustic model, dictionary, and language model files.

majority of tokens belong to very few signs (most only one). They are therefore ideal for quickly pinpointing the user's location.

Signs in a small area. We show that if the search is confined within a small area, the number of signs decreases significantly. We randomly pick 50,000 locations in London. For each location (x_i, y_i), we count the number of signs within $(x - x_i)^2 + (y - y_i)^2 \leq R^2$ where the radius R ranges from 100m to 6.4km. Figure 5 shows that the number of signs decreases accordingly as the search area becomes smaller. Note that in the incremental update phase, which is the common usage scenario compared to the bootstrapping phase (§3.3), usually the search area is small.

5.2 Localization Algorithm

We evaluate the performance of the proposed localization algorithm for different levels of speech recognition accuracy (70%, 80% and 90%) and with difference numbers of input signs (from 3 to 5). We show the results for the New York City and London OSM data sets in Figure 6. We randomly select 5,000 user locations in London and 500 user locations in New York City (the London OSM data set is denser than NYC). Based on Table 3, we only consider user locations with more than 10 signs within 100 meters and thus we set D in Algorithm 1 to be slightly larger than 200 meters. The estimated location is considered accurate if the distance between the user location and the centroid of the selected signs is less than $D/2$. Note this does not imply the localization accuracy is $D/2$. Instead, it intuitively means the selected signs are indeed what the user sees. We run the simulation 5 times and report the average and standard deviation for $T = 4$. There are two major observations from Figure 6. First, better speech recognition can improve the performance of localization. Second, more input signs can lead to better localization accuracy. Even when the speech recognition accuracy is 70%, the proposed algorithm works for more than 90% locations with 4 signs and more than 99% locations with 7 signs.

5.3 Speech Recognition (SR)

Methodology. We adapt one popular implementation of a SR chain called Sphinx [3]. We use its Android version (PocketSphinx) and make use of the acoustic model as it is. In the experiments, we first randomly pick a set of locations in London and NYC. Then, for each location, we collect token sets from the OSM data with different radii (100m∼6400m). Each token set has 67∼4186 tokens for London and 12∼1038 tokens for NYC. We take each token set as input and generate a dictionary and language model, which are then used by one experimental trial. In each experiment, the participant randomly takes a word from the *phones-words* dictionary and pronounces it one at a time. The software presents 10 potential candidates. If there was a correct answer, we treat it as a successful recognition. Otherwise, the participant repeats the word again. When he gets a success, we record a rank of the correct candidate suggested by the recognition system.

Results. We first take a look at the storage overhead imposed by having a phonetic dictionary and a language model and verify that it is very small. Specifically, for the NYC dataset, the dictionary

has sizes 203 bytes∼8 kbytes (100m, 6400m respectively) and the size of the language model is 703 bytes∼15 kbytes. In case of the London dataset, the dictionary size is 701 bytes $\sim$ 31 kbytes and the language model size lies in 1.6 kbytes $\sim$ 63 kbytes.

We next examine the recognition performance of SR shown in Figure 7. It is worth mentioning that the results can be the worst case performance since the participant for the experiment was a non-native English speaker and we use the recognition software out-of-box *i.e.,* we did not tune the default acoustic model or the dictionary/language model generated by PocketSphinx. Overall we think the results are encouraging. Up to 400m radius, repeating once more *i.e.,* 2 trials in total, gives 95% of recognition rate. Even for all other cases, 4 trials will cover 90% of accuracy. We note that this is very preliminary result and plan to do a more comprehensive evaluation with a diverse set of participants and more optimized software settings later *e.g.,* using better trained acoustic and dictionary/language models, as well as improved feature acoustic extraction techniques [18].

We also measured the energy consumption of the SR component and compare it with that of GPS sensor. We use Monsoon Power Monitor [4] and Samsung Galaxy S4 device for the measurement. The SR component (including both microphone and SR processing) consumes ∼44% less instantaneous power compared to that of GPS (369.22 mW vs. 208.48 mW), which fortifies our use of SR.

6. RELATED WORK

GPS has been used as a primary source of location information and provide accurate data in an outdoor environment. But not all mobile devices are equipped with GPS (Table 1) due to concerns such as energy consumption. Further, GPS sensing does not always provide a precise location in urban environment. It is highly susceptible to obstacles in the sky and can have errors as high as more than 100 meters [16, 21]. Recently a technique for acquiring GPS signal in indoor environment has proposed [19]. However it is not yet applicable to the off-the-shelf devices due to the use of specialized radio components and complexity of the system.

In the last decade, numerous research efforts propose localization techniques based on radio signal based fingerprinting. These include ones based on GSM signal [20], Wi-Fi signal [7], FM signal [8] *etc.* Unfortunately, some of them are based on the information that is in general not available in off-the-shelf mobile devices [20] or requires heavy training [7]. In contrast, our system uses microphone (or on-screen keyboard) as input, which is mostly available in today's mobile devices including wearables and our sign database is relatively easy to construct compared to abovementioned techniques. A number of works aim to strategically combine multiple approaches [21, 15, 25, 14, 22]. They tradeoff location accuracy with other system resources, such as energy, thereby different from our approach where the focus is to provide purely local localization systems based on human perception.

When it comes to dealing with textual signs, one intuitive approach is to use image-based positioning [24] *i.e.,* let the device see what a human sees. Although the approach is complementary to our system, it requires multi-stage CV algorithms and large databases (*e.g.,* 300K images for 50K locations at NYC [24]), making cloud the best place for performing such tasks. It thus requires Internet connectivity and brings additional concerns of delay [13], energy consumption, and cellular data usage. Light and viewing angle can significantly reduce the image matching accuracy.

Although explored in slightly different context, the idea of leveraging human assistance to determine a location had been explored and inspired our work. In the GUIDE tourist guide system [9], a visitor is shown several thumbnail images of local attractions and asked if any of them matches the visitor's surroundings. This approach is not directly applicable to a general-purpose localization system like ours due to scalability issues.

7. CONCLUSION AND FUTURE PLAN

As discussed in §6, there have been a large number of indoor and outdoor localization proposals using various sensing techniques. Instead, we provide a solution for offline localization without using GPS, Wi-Fi, cellular, or Internet connectivity, by exploiting human users' perception of nearby textual signs. It enables several important use cases, such as offline localization on wearable devices, in both outdoor and indoor environments. Currently we are working on *(i)* prototyping on Google Glass using speech recognition as the user interface, *(ii)* building a city-level sign database by tagging Google street view images using crowdsourcing, and *(iii)* improving speech recognition accuracy, before conducting field trials.

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