

# MobiCeil: Cost-Free Indoor Localizer for Office Buildings

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## ABSTRACT

Location awareness of people inside commercial establishments can help with occupancy-based dynamic energy management and indoor navigation. In this paper, we propose *MobiCeil*, a novel phone-based indoor localization technique. The proposed technique is offline, automated, and uses image captured from phone's camera to identify the unique ceiling structure of any particular location in the office building. The proposed method is based on these assumptions: (a) in office, employees tend to keep their phones lying on the table, and (b) the layout of ceiling landmarks in a portion of the ceiling structure (as captured by the phone's camera on the table) is unique. We validated these assumptions by checking the phone placement of 47 employees randomly at their cubicle or meeting room, and collecting ceiling layout data from 18 meeting rooms and 6 cubicles in an IT office building. To evaluate the performance of *MobiCeil*, we collected images of the ceiling as seen by the phone (front and back) camera in three different rotations of the phone placed on the table, to capture a total of 960 ceiling images. Our approach achieved an accuracy of 88.2% for identifying locations, with a low computation time of 2.8s per image.

## Author Keywords

Indoor localization; smartphones; workplaces; office buildings; occupancy-based energy management; indoor navigation; camera; ceiling tracking; computer vision.

## ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous

## INTRODUCTION

An Indoor Positioning System (IPS) identifies and tracks the location of object/people inside a building. Location awareness positively impacts the quality of operation in commercial establishments, specifically occupancy-based load scheduling in commercial buildings. Office buildings

consume 40% of the overall energy consumption [1]. Thus, enhancing operational efficiency of commercial buildings have dual advantage of cost mitigation and environmental sustainability. Employee occupancy information can enable various applications, such as dynamic thermal load management, optimizing seat allocation, and sending printouts to the nearest printer. Moreover, it can also help with indoor navigation, *e.g.*, to find the way to the nearest washroom or fire exit, or to a particular room or cubicle.

For outdoor environments, GPS-based positioning system [2] offer the maximum coverage, and hence are widely used. However, GPS-technology fails for indoor environments, due to lack of line-of-sight communication of the device with the satellites. Indoor environments are highly complex. Occurrence of multi-path effects due to building geometry and mobility of people, along with errors caused by interference from other wired and wireless networks in the vicinity, pose significant challenges in the design of indoor positioning systems.

Several techniques for indoor positioning have been proposed, based on infrared (IR) [3, 4, 5], radio-frequency identification (RFID) [8], wireless network (WLAN) [9, 10], Bluetooth [11], and camera image analysis [12, 13, 14, 15, 16]. However, IR-based solutions and sensor networks require additional hardware installation, while RFID-based systems are less accurate due to limited range and multi-path effects of the building. Vision-based techniques tend to be computationally intensive making them unsuitable for real-time applications. Therefore, design of an IPS involves a tradeoff between computational requirements, infrastructure deployment and positioning accuracy.

With the observed growth in smartphone penetration, and increasingly sophisticated inbuilt sensors and computational capabilities of modern smartphones, there is an opportunity to explore smartphones as a platform for IPS. WiFi and Bluetooth based solutions for indoor localization using phones have been investigated [17], but not commonly used due to low accuracy. With increasing phone size, people tend to keep their phones lying on the table when the phone is not in use, with the phone's front or rear camera facing the ceiling. From our collected data, we found 76.5% employees keeping their phones on the table at their cubicle or meeting room. This image from the phone's camera can be used to identify the phone's location, using the unique ceiling layout. We collected ceiling data of 18 meeting rooms and 6 cubicles of an office building and found that

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each 3x3 tiles (equivalent to the number of tiles captured using phone's front camera on the table) layout was unique.

In this paper, we propose *MobiCeil*, a novel phone-based offline, low complexity, automated indoor localization technique. It uses image captured from phone's camera to identify the unique ceiling structure of any particular location in the office building. On a dataset of 960 ceiling images, our proposed approach achieved an accuracy of 88.2% for identifying locations, with 2.8 seconds of computation time.

#### RELATED WORK

Several technologies have been explored to design indoor location sensing systems. We will discuss the three most common classes of IPS here: Infra-Red (IR) based, Radio Frequency (RF) based, and Vision-based technologies.

*Infra-Red* (IR) based positioning systems are the most commonly used. Typically, IR-based system provides absolute position estimates by establishing line-of-sight communication between transmitters and receivers. Active badge system [3] performs position sensing by sending an IR signal to one or more sensors located in a room or a zone and updates location information on the central server. Firefly system [6] models motion of an object by locating IR emitters in the form of small tags. Although IR sensors are cheap, the additional hardware requirement increases the cost significantly, and adds to the complexity of hardware deployment. Also, the limited coverage area negatively impacts the accuracy of IR-based systems.

*Radio frequency* (RF) waves can travel through walls and human bodies, thus significantly increasing the coverage area. Typically, RF-based positioning systems reuse the existing RF infrastructure (such as WLAN, Bluetooth), making the deployment of RF systems convenient and inexpensive, compared to IR-based systems. WLAN-based positioning systems [8, 9, 10] use the existing wireless network for detecting position in indoor environments using the triangulation technique. However, such solutions suffer from major performance issues due to the complexity of indoor environments, and are also limited by the requirement that objects being tracked needs to be equipped with WLAN technology. Bluetooth [11] technology has also been explored as a potential IPS platform, but due to its limited range and delay involved in the response time, it has not been adapted.

*Vision-based* positioning systems does not require the objects being tracked to be equipped with any sensor. Easy Living [12] uses two stereo cameras to identify objects and even estimate their position. Other techniques such as ambience fingerprinting [13], SLAM [14], 3-D modelling using RGBD-cameras [15] attempts to model the indoor environment by tracking landmarks in an iterative manner. However, deploying cameras in a large area is expensive. The ubiquity of smartphones with inbuilt high resolution cameras has driven the research of using them for indoor positioning. Most of such research work makes an implicit

assumption that location of the smartphone is a good proxy for the location of the person using the phone. We agree with the assumption and use it in our proposed technique as well. Ravi *et al.* [16] proposed a system wherein people carry phone as a pendant to take images for location identification. Users mentioned discomfort in carrying the phone as a pendant. LuxaPose [21] use modified LEDs to encode their locations in optical pulses. It requires extra hardware to be deployed on the ceiling for indoor tracking [21]. Furthermore, phones have limited computational capabilities, thus indoor localizer systems requiring extensive computations usually depends on external computational infrastructure to provide real-time location information.

In this work, we propose a phone-based indoor positioning system using vision-based technique, that requires low computation which can easily run on a smartphone.

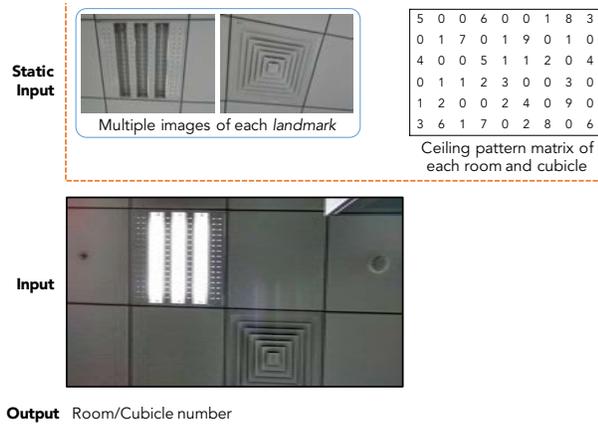
#### THE MOBICEIL SYSTEM ASSUMPTIONS

The *MobiCeil* system utilizes smartphone when it is lying idle on the table to capture images using the phone's front or rear camera (whichever is facing the ceiling). The proposed approach is based on three key observations. First, usually office buildings have a standard set of ceiling landmarks, such as HVAC vents, lights, motion sensors, microphones, WiFi routers, etc. This reduces the complexity of landmark identification as the search space gets reduced significantly. Second, ceiling design of different rooms or cubicles have a tiled layout (Fig. 1), wherein the layout of landmarks in a portion of the ceiling structure is unique. This ensures no ambiguity in identifying location corresponding to the input ceiling image. Third, with the increasing phone size, employees tend to keep their phones on the table while working in their cubicle, or brainstorming in the meeting room. To validate these observations, we collected two different datasets.

#### Ceiling Layout Data

Two researchers manually collected ceiling layout data from 18 rooms and 6 cubicles in an IT office building. All 18 meeting rooms in a particular floor were used. The ceiling layout has a tiled design with each tile measuring 1.9ft x 1.9ft. The researchers noted down the landmarks on the ceiling (of height 8.3ft from floor), thus creating a matrix of integers for each meeting room and cubicle, with each integer representing a tile landmark. We call this *ceiling pattern matrix* (Fig. 1).

From the ceiling layout data, we found that each meeting room had 36.75 tiles on an average (standard deviation = 14.5, minimum = 20, maximum = 70 tiles/room). For cubicles, 16 tiles in a 4x4 ceiling layout just above the cubicle were noted. In total, across the rooms and cubicles, 17 unique landmarks were identified. Each landmark was assigned a unique integer between 1 to 17. The three most commonly observed landmarks were empty tiles (30.8%), HVAC vents (12.3%), and lights (16.5%, consisting of 3.5% small lights, 5.6% medium lights and 7.4% big



**Figure 1. MobiCeil system with the format of static input resources, input image, and output room/cubicle number.**

lights). Other prevalent landmarks were sprinkler (5.3%), audio speaker (3.3%), smoke detector sensor (4.4%), motion sensor (3%), and wireless network router (2.3%). Each room had 10.53 distinct landmarks on an average ( $\text{std}=1.2$ ,  $\text{min}=9$ ,  $\text{max}=14$ ), while each cubicle had 7.8 distinct landmarks ( $\text{std}=0.75$ ,  $\text{min}=7$ ,  $\text{max}=9$ ). On analyzing this data, we found that no  $3 \times 3$  sub-matrix of the matrix representation of the complete ceiling layout, matches with that of the other. This verifies our assumption of uniqueness in ceiling layout across rooms and cubicles.

#### Employee Phone Placement Data

We collected data to validate our assumption that employees tend to keep their phones lying on the table while working in office. Two researchers randomly went around the office (at 11 am) and noted the phone position of 47 employees – 25 of them were working in their cubicle, while 22 were found to be working in 6 different meeting rooms in a group of 3-5 people. From this data, we found 76.5% employees (19 out of 25 employees in their cubicle, and 17 out of 22 employees in meeting rooms) had their phones lying on the table, hence proving our assumption.

#### THE MOBICEIL SYSTEM ALGORITHM

The MobiCeil system use the images captured by the smartphone's camera as input (Fig. 1). In addition, the system requires two static input resources that needs to be provided only once during the setup – (a) multiple images from different perspective of each ceiling landmark, and (b) ceiling pattern matrix of each meeting room and cubicle (Fig. 1). The database of images of ceiling landmarks is needed for landmark recognition. Ceiling pattern matrix can be conveniently obtained manually, or can be also obtained from the ceiling layout design provided by the architect/designer to the building management authorities. Using the input image and static input resources, the system outputs a room or cubicle number.

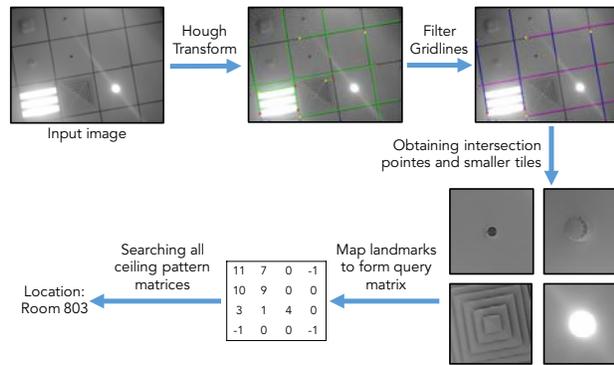
The proposed algorithm (Fig. 2) consisted of three major components. The initial step involved obtaining gridlines to extract each tile in the input ceiling image. After that, the

landmark on each tile was identified to obtain a *query matrix* representation of the image. Finally, this query matrix of the input image was queried over the dataset containing the ceiling pattern matrices of all the meeting rooms and cubicles under consideration. The search query involved finding the meeting room or cubicle having a ceiling pattern matrix containing the query matrix as a sub-matrix.

*Tiles Extractor:* Under the assumption of a tiled ceiling layout, we attempt to find quadrilaterals in the ceiling image using parallel gridlines representing a tile. To extract lines in an image, we used Hough transform [18] (Figure 2). Note: If the wide-angle of phone's camera adds noticeable distortion, the images need to be rectified. In our case, no rectification was needed. Most of the images contained many spurious lines, thus requiring further processing to filter out gridlines. The lines obtained can be divided into two sets of parallel lines,  $S_1$  and  $S_2$ , with each line in  $S_1$  being perpendicular to the lines in  $S_2$ . Each set is evaluated separately to obtain the gridlines by computing the distance between the lines. Lines with distance equal to estimated width of a tile, formed the gridlines. The intersection points of lines in  $S_1$  with the lines in  $S_2$  provided full quadrilaterals representing a tile. The intersection points of  $S_1$  and  $S_2$  with the image boundaries provided incomplete quadrilaterals, showing incomplete captured tiles. Incomplete tiles with an area less than half of the complete tile were ignored, as they do not capture enough relevant information.

*Landmark Detector to Generate Query Matrix:* The second step involved mapping each tile to a landmark with high confidence. To ensure rotational and scale invariance, we used SURF [19] to obtain feature descriptors. To classify which landmark each tile resembles to, we trained a multiclass binary SVM classifier using the Error-Correcting Output Codes (ECOC) framework [20]. Recent research showed that ECOC framework successfully deals with the problem of modelling multiclass classification problems using a set of binary classifiers and to combine them. The SVM classifier used the static input images (Fig. 1) as training set, which consisted of 72 images for each of the 17 landmarks, thus totaling to 1224 images. Each ceiling landmark was considered as a separate class. Each landmark corresponds to a unique integer, thus the grid of tiles was represented as a matrix of integers, referred here as *query matrix* (Fig. 2). Note: -1 got assigned to incomplete tiles.

*Location Identifier:* The query matrix retrieved is then queried over a database of ceiling pattern matrices, which was provided at setup as part of the static input (Fig. 1, 2). Ceiling pattern matrix of each meeting room and cubicle is scanned to check if they contain the query matrix corresponding to the input image. If there is a sub-matrix match found, the system outputs the location information, in the form of meeting room/cubicle number.



**Figure 2.** Image processing based method to compute the location of an employee using the input ceiling image.

### Data Collection

In order to evaluate the performance of the proposed MobiCeil system with respect to accuracy and computation time, we collected data in an IT office building in India. Data was collected from 18 meeting rooms and 6 cubicles.

To start with, two researchers manually collected the static input data (Fig. 1) – (a) 72 images of each of the 17 unique landmarks, and (b) ceiling pattern matrix of the 18 meeting rooms and 6 cubicles. The landmark images were captured by placing the phone on the table (of height 2.4ft) directly below the landmark tile and below each of the 8 tiles adjacent to the landmark tile. This was repeated with both the front and back camera of the phone, and with the room/cubicle lights in On and Off state to account for the glare in images. Note: Even in the light Off state, each room/cubicle has one or more emergency lights that cannot be turned off, to avoid the room/cubicle getting completely dark. This whole process was performed twice. That comprised of 72 images (9 tile positions x 2 cameras x 2 light modes x 2 images) per landmark, totaling to 1224 images (72 images/landmark x 17 landmarks). Each image was then cropped to extract the landmark tile image, and resized to 255 x 255 pixels. The process to identify ceiling layout and generate ceiling pattern matrix has been described in section *The MobiCeil System Assumptions*.

To generate the test dataset, we collected 960 ceiling images. Out of the 18 meetings rooms, 10 were medium sized rooms with the maximum capacity of 5 people, while 8 were small sized rooms with the maximum capacity of 3 people. The ceiling test images were captured by the researcher, by placing the phone on the meeting room table in front of each chair, in three different rotation angles of 0, 30 and 60 degrees. Again the images were taken with both the front and back camera, and with the meeting room lights in switched On and Off state. For cubicles, a similar approach was followed. Hence in total 960 test images ((10 medium rooms x 5 chairs x 3 phone rotations x 2 cameras x 2 light modes) + (8 small rooms x 3 chairs x 3 phone rotations x 2 cameras x 2 light modes) + (6 cubicles x 3 rotations x 2 cameras x 2 light modes)) were collected from the meeting rooms and cubicle. All the images for both the

test data and static input were captured using a Motorola Moto G2 phone with 8MP rear camera (aperture: f/2.0) and 2MP front camera (f/2.2).

### RESULTS

We evaluate the performance of MobiCeil in terms of accuracy and computational complexity. The static input of 72 images of each of the 17 unique landmarks, and ceiling pattern matrix of the 18 meeting rooms and 6 cubicles, were provided to the system at setup. Ceiling pattern matrix data also served as the ground truth data. The input test data consisted of 960 ceiling images.

The overall accuracy of the system in determining the location was 88.2%, which is reasonable for a low-cost, offline, low complexity, automated indoor localization system, with the use case of energy management and indoor navigation. Exploring further, we found statistically significant differences in the accuracy for the images captured using the front versus back camera, and also for the images in lights On versus Off mode. The best performance was achieved by images from the back camera with lights of the room/cubicle in the switched Off state (94.5%), while the worst performance was with front camera images in lights On state (81.6%). Images from the phone’s front camera achieved an accuracy of 84.7%, while images from the back camera were 91.6% accurate. This was expected as back camera has a higher resolution of 8 MP while front camera has only 2 MP resolution. Interestingly, images taken with the room/cubicle lights Off were found to be 91.25% accurate, while images with lights On achieved an accuracy of 85.2%. Lights resulted in a lot of glare, which impacted the accuracy of the landmark detection algorithm. We did not find any significant difference in the test images with different rotations ( $p>0.05$ ). This may be because of SURF, which is rotation invariant. Also, no significant difference was found between the images from meeting rooms and cubicles ( $p>0.05$ ).

On an average, the tile extractor module took 0.8s (std=0.2), the landmark detector to generate query matrix took 1.3s (std=0.3), and the location matching using ceiling pattern matrix took 0.7s (std=0.1). Thus overall it took 2.8s per image for indoor location computation (std=0.5).

### DISCUSSION

The proposed system, MobiCeil, aims to infer location of the user inside the office building, using the ceiling images captured from the user phone’s camera. One of the major advantages of the system is that it captures and processes the input image offline with no user intervention. The underlying algorithm of the system employs scale-invariance as well as rotation-invariance image processing techniques. Also, a few key observations, such as uniqueness of the arrangement of landmarks on the ceiling and existence of a fixed set of ceiling landmarks, lead to significant increase in the accuracy and reduction in the computational complexity. However, this also limits the scope of MobiCeil.

There are several limitations of the proposed approach. First, it will work only for buildings with tiled ceiling layout, with unique ceiling layout in different zones (including meeting rooms, cubicles, and recreational area) of a floor. We validated this uniqueness assumption by collecting data from a single floor of a building, however more data from different buildings needs to be collected to strengthen this assumption. MobiCeil can work on the other floors of the same building, as the whole building had a similar tiled ceiling layout. Second, the system requires the phone to be on the table, which may not be always true as it can be in user's pocket, bag, or in his/her hand. This constraint can be identified as a feature, *i.e.*, users can avoid being tracked by keeping the phone in the pocket/bag, or covering the camera lens. Using collected data, we showed that most employees tend to place their phones on the table in an office environment. In future, the MobiCeil system can be enhanced by using other wireless technologies (such as Bluetooth or WiFi) to identify people in a group setting or devices in close proximity. In such cases, not all individuals need to be localized using the camera image data, thus reducing the dependency on phones lying on the table assumption. Third, the whole system was evaluated only on a single floor of a building. More deployments are needed to build a strong case to prove the generality of the proposed approach. Fourth, camera images can trigger privacy concerns among the employees. There are multiple ways to resolve it – the phone application must take explicit user permissions to access the camera in order to capture the ceiling images. Also, images must be automatically captured only when the user is inside the office (which can be known using the GPS data) and only when the phone is static on a flat horizontal surface (which can be known using the phone's accelerometer and gyroscope sensor data). This will also help in reducing the phone's battery consumption by MobiCeil, and completely removes any required user intervention. Fifth, our evaluation did not consider partially obstructed view of the ceiling (*e.g.*, when the phone is placed close to another object or user). This needs to be evaluated in future. Last, the system was tested with a single smartphone. Different phones have varying camera lenses, which may add different kinds of distortions. Hence image rectification can help before applying the Hough transform.

In spite of all these limitations, the system evaluated on 18 meeting rooms and 6 cubicles in an IT office building, showed an accuracy of 88%. The accuracy and computation time can be further improved by modifying the algorithm for processing of the input image. For instance, the current system does not take into account the artifacts observed due to inappropriate lighting conditions. Advanced image processing techniques can help in detecting and removing such artifacts. We plan to pursue such enhancements as future extensions of this work. Moreover, to tackle the tedious bootstrapping issue, MobiCeil can crowdsource it, by prompting the user to enter their location when no match has been found (yet) for the observed ceiling pattern.

Finally, this approach might also work for other patterned ceilings, *e.g.*, wooden ceilings. Future work is needed in that direction.

## CONCLUSION

This work presented a low complexity phone-based indoor localization technique that performs offline computation to obtain location information of the user. The proposed MobiCeil system automatically takes an image using the front or rear camera of the phone when it is in a static horizontal position, and identifies the location based on comparison of the ceiling landmark information fed into the system as static input resources at the time of setup. An evaluation shows the system achieves a high accuracy of 88.2% for identifying locations, with a low computation time of 2.8s/image. Such a system can help in reliable occupancy detection in an office environment, which has several applications, such as dynamic energy management and indoor navigation.

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