

Boat Arrival Time Prediction System using Mobile Phone Sensing

Phuthipong Bovornkeeratiroj, Kulit Na Nakorn, Kultida Rojviboonchai*

Department of Computer Engineering
Faculty of Engineering,
Chulalongkorn University
Bangkok, Thailand

Phuthipong.B@student.chula.ac.th, Kulit.n@student.chula.ac.th, Kultida.r@chula.ac.th

Abstract—Boat is one of the most popular vehicles for local people and tourists to travel in Bangkok, Thailand, since there is no traffic jam. Without accurate arrival time, however, boat becomes an inconvenient transportation since the waiting time can be varied from 10 minutes to an hour. In this paper, we propose a novel boat arrival time prediction system by using passengers' mobile phones. The system can work without installing any infrastructure on boat or pier. It does not require cooperation with any boat company. This would make the system almost costless and easy to implement. Moreover, the system does not require any manual input from the passenger, so this means it can automatically predict the arrival time. We take advantages of the boat environment and design the system to use only energy-efficient sensors, including Wi-Fi, accelerometer, and microphone. No energy hungry sensor such as GPS is used. The system has been tested with one of the most crowded boat transit, Chao Phraya Express Boat, in Bangkok, Thailand. The result shows that our system can predict boat arrival time accurately. Specifically, the prediction error is less than one minute per pier.

Keywords—boat; transit; arrival time prediction; mobile phone; energy-efficient sensor;

I. INTRODUCTION

Bangkok, the capital city of Thailand, is one of the most traffic jam city in the world. With an increasing of million cars every year [1] and ineffective responses to the congestion, such as building new roads and widening existing roads, make the traffic worsen every year. People start to adapt themselves with the bad traffic by using alternative transportations, such as boat or train. Boat, the traditional transportation that has been used for decades, comes with a good traffic, and surprisingly provides more reliable travel time than the bus.

The most massive used boat in Bangkok, Chao Phraya Express Boat, has 35,000 - 40,000 passengers per day [2]. It has 62 boats in their fleet with 34 piers to support people all around the city, and cover distance of 32 kilometers. This make boat undoubtedly becomes one of the most important transportations in Bangkok.

Yet boat still has the problem discouraging people from using that is the unknown arrival time. The arrival time of the boat, such as Chao Phraya Express Boat, can be varied from 10

minutes to one hour in the worst case. Though boat company has also provided a fixed timetable at every pier and on its website but the given information allow a passenger to know only a period of time, not the exact time. For example, orange flag boat on the weekend will come every 20 minutes. Another option that the passenger has is Google Maps, which also provide the same information, that is every 20 minutes. This information is good to know but it is not practical, and unreliable. Since there are many factors that can effect the arrival time of the boat such as river condition, weather condition, number of passengers, boat drivers who never follow the time table, accident, or traffic that occurs sometimes. The accurate boat arrival time will not only provide satisfactory of the boat passenger but also encourage people to choose boat instead of bus. To implement such a system, normally the cost is relatively high for both installation cost and maintenance cost, and the cooperation with the boat company is needed. Hence, we propose a boat arrival time prediction system that is cheap and does not require the cooperation from the boat company.

Our boat arrival time prediction system uses passengers' mobile phones. Other prediction systems that need human input are easy to implement but hard to maintain. To encourage people to keep updates their boat's location and status is difficult. Moreover, manual input by human can sometimes lead to human error and fraud. To avoid these problems, our proposed system can work automatically without user effort by using the available sensors in passengers' mobile phones. Still there is a drawback of an autonomous system that it needs to active some sensors all the time to keep detecting. To overcome battery drain problem, battery hunger sensor, GPS, is not used in our proposed system. Instead, the energy-efficient localization sensors are chosen to replace the GPS. Energy-efficient localization technique has been proven that it works well with the predictable path and consumes less power than GPS [3]. This is suitable with boat's characteristic since the river is not complicated comparing to road. In summary, the sensors that are used in our proposed system to predict the boat arrival time are microphone, accelerometer, and Wi-Fi.

Our system utilizes the mobile phone's sensors to capture the necessary information from the passenger's environment,

*Corresponding author

and then try to predict the arrival time of the boat. Before the system can predict the arrival time, it must complete the following detections: (1) On-Boat Detection: the system can determine whether user is on the boat or not. After the system knows that user is on the boat, other detections will start. (2) Boat-Stop Detection: the system can detect which pier the boat stops and collects a sequence of those piers. The sequence of the piers will be used for other detections. So if the boat-stop detection is not accurate, it will affect other detections' accuracy as well. (3) Boat-Direction Detection: in case that the boat service has more than one direction. The system must be able to detect the direction of the boat such as forward or backward. Without the direction of the boat, the boat arrival time cannot be predicted. (4) Boat Classification: boat may have more than one route so the system should be able to differentiate which route the user is on. Finally, our system will use all the detected information to predict the boat arrival time.

Our proposed system has been implemented and tested on Android mobile phones. In our experiment, we have used data collected from Chao Phraya Express Boat, the most used boat transit in Thailand. Figure 1 illustrates boat and map of Chao Phraya Express Boat.

The rest of this paper is structured as follows. In section II, we summarize related work, including arrival time prediction and energy-efficient localization technique. Then, in section III, how our system works is explained in detail. In section IV, performance evaluation is shown. Finally, section V concludes our paper.

II. RELATED WORK

Transit arrival time prediction on bus or train system is very closed to our work. We studied them and tried to apply the methodology that works with bus or train to our boat arrival time prediction system. However, some characteristic of boat, bus, and also train are different so we have to adapt and innovate new methods.

Easy Tracker [4] is a real-time bus tracking using GPS in mobile phone. The mobile phone is required to be installed in each bus. The system not only can predict the arrival time but also can detect the bus stop automatically. Although the result is good, the system needs mobile phone to be installed in every bus.

Cooperative Transit Tracking using Smart-phone [5] is a crowd-sourced real-time tracking. It can track both bus and train by using GPS, Wi-Fi, and accelerometer combined with

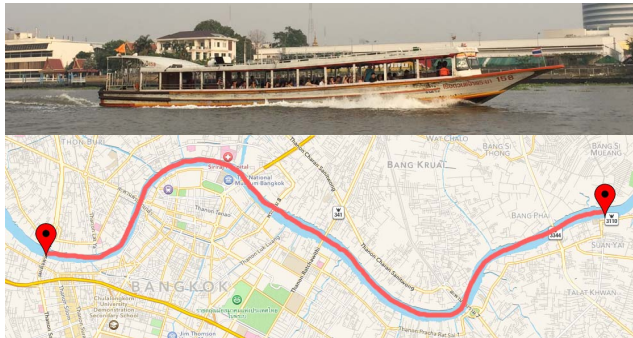


Fig. 1. Boat and map of Chao Phraya Express Boat

Hidden Markov model. The system is tested with the simulated Chicago transit network. Battery usage from the GPS enabled is still high, even the system tried to limit the GPS usage.

Real-time trip information service for a large taxi fleet [6] demonstrates the system that can provide expected fare and trip duration for each ride that the passenger is going to take. The system needs a huge amount of historical data to be able to accomplish the goals.

Tiramisu [7] focuses on crowdsourcing to get the information about bus location, predicts the arrival time, and also reports problems. However, users have to manually fill all the information.

How Long To Wait [8] is a bus arrival time prediction with energy efficient localization. It uses cell-tower sequence to find the bus location and classify bus route. The system detects the user being on bus by using sound of RFID reader and differentiates bus and train with accelerometer. The performance is very good and battery consumption is low. Still the system is for bus, not for boat.

In term of energy-efficient localization, there are many works that already tackle this topic and come up with a good result. GAC [9] is a hybrid approach framework. It combines GPS, accelerometer, and compass to reduce the usage of GPS in the framework. It can slightly reduce energy drained. EnLoc [3], a non-GPS localization for mobile phone using only GSM and Wi-Fi, works well in predicted path and consume only half amount of energy compared to GPS-usage framework. Both of them can give an accurate location and consume less energy. Energy-Efficient Positioning [10] uses Cell-ID sequence matching technique to estimate current position of the mobile, although the pair of cell-ID and GPS position is needed. Did you see Bob? [11] demonstrates that the system can route to the specific user without using any GPS, or Wi-Fi but with just audio beacon, encounter record and learning the individual walking trail. SoundSense [12] shows that sound can be used to recognize events that occur in users' daily life.

From many reviews, we found that none of them can be directly applied for supporting the boat arrival time prediction.

III. SYSTEM ARCHITECTURE

In this section, the components of our system are shown and each technique for boat arrival time prediction is described in details.

A. System Overview

Figure 2 shows the major component of our system and function of each component inside. We divide our system into 3 parts: Mobile, Server and User.

Mobile part: Mobile tasks can be considered as a scouter for the system. As a scouter, mobile is assigned to seek and collect all necessary data for the prediction and send it back to the server. As depicted in Figure 1, data that the mobile has to collect are Wi-Fi, accelerometer and audio. The only process on the mobile side is on-boat detection. When the state is changed to on-boat state, it starts sending the data to the server. When the state is not on-boat state anymore, it stops sending the data.

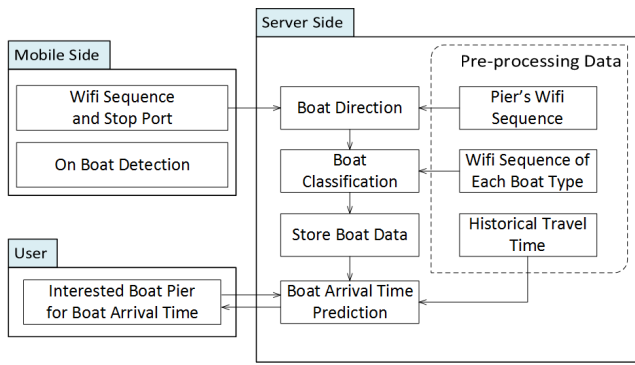


Fig. 2. System Architecture

Server part: the server does all the hard work. The entire processing task is shifted to the server as much as possible to reduce energy consumption on the mobile side. All data is sent to the server, collected, and then processed to get the arrival time of the boat. Apart from data that was sent from mobile, the server needs pre-processing data to be able to process the arrival time. The pre-processing data is required to pre-store inside the server and mobile for the future calculation. The data are Wi-Fi of each pier, travel time between each pier, and pier sequence. For Wi-Fi at each pier and average travel time between each pier, we have to collect manually in advance. For the pier sequence, it is a static data so we can get it from the boat company's website directly. Then we create a database to store the gathered data after pre-processing them into an easy-to-use format.

User part: the user has to send his/her interested pier that he/she wants to know the arrival time to the server. And the server is going to calculate the predicted arrival time of any boat that is going to the interested pier.

After the server gets data from mobile, it begins to check that the boat direction and the boat type are already known. If direction or type is not known yet, the server tries to detect with the data recently received. Then the boat location is updated according to the recent data. Finally, the boat location is stored in the server with the last updated timestamp.

B. On-Boat Detection

To detect whether the user is on boat or not is the first stage before triggering other detections as shown in Figure 2. Incorrect on-boat detection can lead to system failure since no data is sent to the server. So to make it works correctly, we need to understand how boat works and how passengers act when they embarks.

Chao Phraya Express Boat normally has captain, who drives the boat, and conductor, who gives a signal when the boat should stop or leave the pier and collects fee from the passengers. The interesting point here is that every time when the boat is going to stop at a pier or leave from a pier, whistle is blew by the conductor to give a signal to the captain. From our observation, it is a standard protocol for every boat that the conductor uses to communicate with the captain.

For the passenger side, they have to queue in line and wait for boat on the pier and when the boat arrives, they walks into

the boat and stand or sit if there is a seat available. Based on our experiment, the time needed for walking from pier to the boat or vice versa is 10 seconds or more.

By combining both boat and passenger behavior, we can list specific actions that will notify our system when embarking is happening. Those specific actions are (1) walking, (2) sitting or standstill (stop walk), and (3) whistle sound. After we know the actions, we have to choose to sensors to detect each action. Walking and stop walking can be detected by accelerometer. And for whistle, it is detectable by using microphone.

The experiment is initiated on our Android mobile phones as mentioned in the introduction part. The accelerometer sensor is used for detecting walking. We record the accelerometer at rate of 20Hz, 5Hz, and 1Hz. The result shows that 1Hz is enough to detect the walking action so 1Hz rate is chosen for recording the accelerometer. Then we record the sound of conductor's whistle with sampling rate of 8kHz and convert them from time domain to frequency domain using Fast Fourier Transform with 256-block size. Figure 3 shows the result of the sound when the whistle can be heard in frequency domain. We can see peaks around 3kHz bands when there is a whistle sound. Comparing with no whistle result, there is no peak at 3kHz.

But enabling audio and accelerometer all the time is wasteful. It can consume a lot of batteries. the system should have something to trigger them. Since a passenger must embark at a pier, it means that we should start on-boat detection when the passenger is at pier. Luckily, we can certainly detect that the user is located at pier using Wi-Fi.

Now our system can detect all the action needed for on-boat detection, but we have to put order for them to make it work systematically. Figure 4(a) demonstrates order of actions for on-boat detection. The detection starts when any pier's Wi-Fi is detected. Then the accelerometer and the microphone will be activated to detect walking and whistle, respectively. The detection will be finished when the passenger stops walking and Wi-Fi is gone since it means that the boat departed away from the pier already.

In contrast with on-boat detection, the system should stop all detection when the passenger leaves the boat. Disembark detection is introduced. The process can be seen in Figure 4(b). It is a reverse version of on-boat detection but simpler since possible action of a passenger on the boat is very limited. Specifically, walking on the boat for a while could mean that the passenger is going to disembark. And pier's Wi-Fi that is detected during walking process will be considered as the destination pier for this passenger.

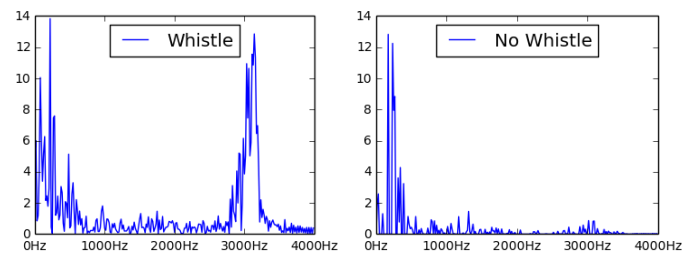


Fig. 3. Comparison between Whistle and no whistle using FFT

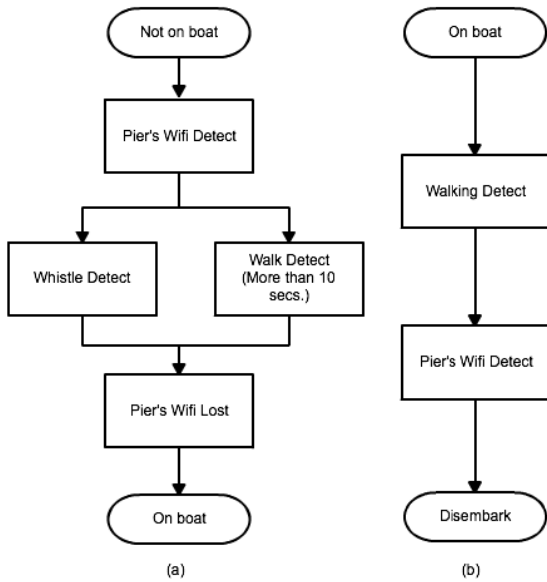


Fig. 4. (a) on-boat detection flow (b) disembark flow

C. Boat-Stop Detection

This detection is the most important part because its result will be used in boat-direction detection, boat classification and boat arrival time prediction. Though we can use whistle sound to detect when the boat is stopped, we still need to find a pier at which the boat stopped.

From the sensors that a mobile phone has, the candidates that can be a solution are cellular and Wi-Fi. We experimented by recording both cellular tower ID and Wi-Fi at each pier with our phones. From the result, comparing each pier with cellular tower ID, some piers have the same cellular tower ID detected. Furthermore, cellular tower ID for each pier changes from time to time based on many factors that effect the cellular tower signal. Such an inconsistency can lead us to a complex system and will limit the system flexibility. On the other hand, for Wi-Fi, all piers have different Wi-Fi detected. As a result, our system selects to use Wi-Fi, not cellular.

However, using only Wi-Fi to detect that the boat stops at a pier can give a false positive result. As shown in Figure 5, the boat just passes “P2” pier without stopping at the pier but the distance of the boat and the pier is closed enough to detect the “P2” pier’s Wi-Fi. This case can lead to a false positive detection. Therefore, instead of using only Wi-Fi, our system uses whistle sound as well. When the whistle sound is detected, the system will check Wi-Fi results and mark as the boat has stopped at the detected pier.



Fig. 5. False Detection Scenario

Though Wi-Fi works very well for differentiating each pier, not all piers have the Wi-Fi. From our experiment with Chao Phraya Express Boat, 3 out of 24 piers do not have any Wi-Fi installed. After we investigated those piers, we found that all three piers are in a low population area. To overcome this problem, we alternatively combine the whistle sound with travel time between each pier to estimate which pier it is when Wi-Fi is not found.

D. Boat-Direction Detection

Direction of the boat is one of the mandatory information that system needs to know before predicting the arrival time.

To find the direction, the results from boat-stop detection and on-boat detection are used. A sequence of two piers is already enough to tell which direction the boat is going.

E. Boat Classification

Alike other transits, the boat system can have many types. Chao Phraya Express Boat has 4 different types of boats, one local line and three express lines (separated by flag colors), as shown in Figure 6. Though they sail in the same route along Chao Phraya River, they stop at some piers differently. This effects on travel time for each type of boats.

Since the route is the same but the boat-stop piers are different, we can use a sequence of the boat-stop piers to distinguish between each type of boats. Figure 6 demonstrates the scenario that can distinguish each type of boats. To perform the boat classification, the server maintains a sequence of boat-stop piers of each type of boats in advance. When the system detects that the boat stops at a pier, the server will compare the sequence of the boat-stop piers with the predefined sequence of each type of boats. If the classification process is successful, the boat type will be recorded and will not process again for that boat.

F. Boat Arrival Time Prediction

Before the system can calculate the arrival time, direction of the boat is required. And for a better accuracy, type of the boat should be known. However, if the type of the boat has not been classified yet, the system is still able to predict the arrival time but with less accuracy.

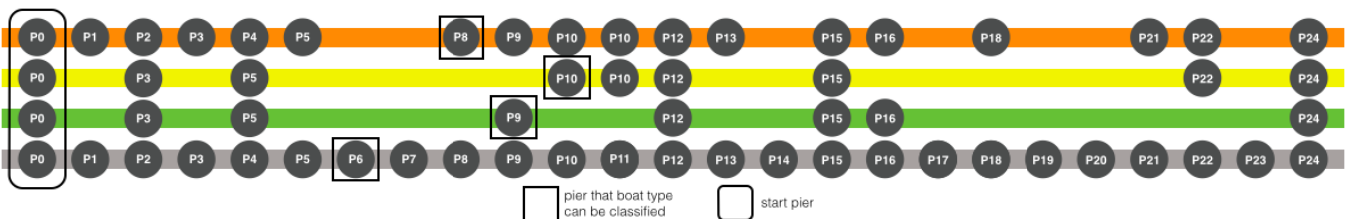


Fig. 6. How the system classifies each boat type using sequence of stop

Since boat traffic is good, the travel time of boat is quite stable which make our system does not need to use a complex algorithm to find the arrival time. To calculate arrival time, the system uses latest status of every boat detected at that time and the historical travel time between each pier, which already pre-store on the server. The server will start calculating the arrival time when there is a request. To estimate a boat arrival time, the system needs to calculate the time of each boat that will arrive at the requested pier.

Figure 7 depicts an example of calculating a boat arrival time in our system. As shown in the figure, the system gets the query for arrival time at “P4” pier and processes as follows: Firstly, our system lists all boats recently appeared in the system, and removes all boats that will not come to “P4” pier from the list. Then, it calculates the estimated time that each boat will arrive at “P4” pier. And finally, it returns the result to the user.

The algorithm to estimate the arrival time of each boat to a specific pier is defined as follows:

$$A(P_d) = T(P_n, P_{n+1}) - (t_c - t_{last\ stop}) + \sum_{i=n+1}^d T(P_i, P_{i+1}) \quad (1)$$

where P_d is the d^{th} pier
 $A(P_d)$ is the arrival time of the boat to the d^{th} pier
 $T(n,m)$ is the time interval that the boat travels from pier n to pier m
 t_c is the current time
 $t_{last\ stop}$ is the time that the boat stopped at the latest pier

IV. IMPLEMENTATION AND EVALUATION

We evaluate our system using Android Phones, Nexus One, to collect the Chao Phraya Express Boat data for 20 trips and use them to test with our proposed system. This section shows performance evaluation of all detections and the boat arrival time prediction in our system.

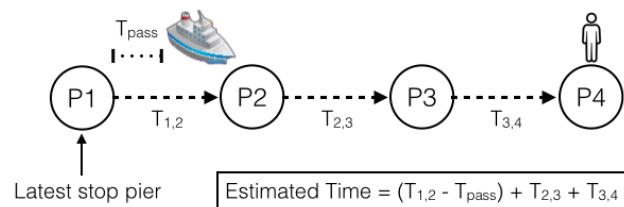


Fig. 7. Boat arrival time calculation

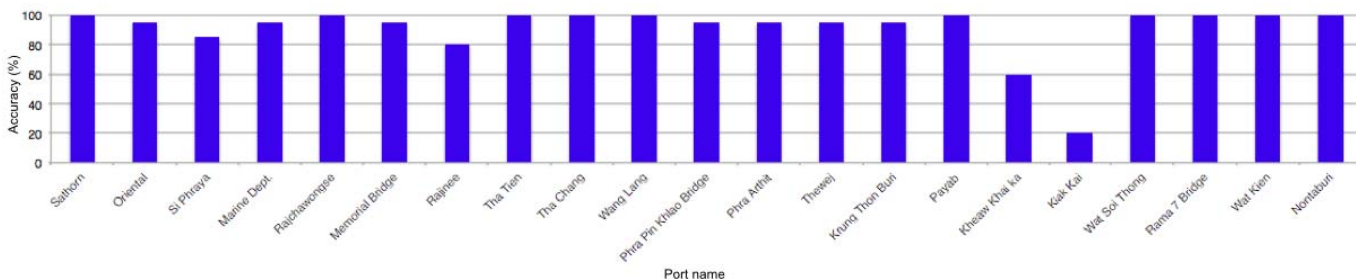


Fig. 8. Boat stop at pier detection accuracy for each pier

A. On-Boat Detection Performance

From 20 records that we collected, we observe that the time that uses to finish the flow is varied based on the number of embarking passengers. If there are a lot of passengers embarking, the walking action will take more time, and it will effect the time that the boat stops at the pier. From our experiment, we found that our on-boat detection can take up to 240 seconds to finish the flow when the pier is crowded. However, this does not effect on the performance of our on-boat detection. Our on-boat detection and disembarking detection can perfectly detect with 100% accuracy. The reason behind this is because the boats and the passengers actually did the actions according to our detection flows.

B. Boat-Stop Detection Performance

To evaluate the detection performance, we manually record at which pier the boat stops while collecting the data. In Figure 8, we plot the accuracy, which our system can detect at each pier. The overall accuracy is approximately 90%. The problem that makes the detection missed is that sometimes the whistle sound is not loud enough and our test devices fail to detect. And there are three piers that are “Rajinee pier”, “Kheaw Kai ka pier”, and “Kiak Kai pier”, which accuracy is lower than others. This is because these piers do not have Wi-Fi and the boats usually do not stop at these piers if there is no passenger who wants to embark or disembark. The last two pier’s results are very poor because their locations are very close in distance. It makes our algorithm, which uses historic time together with whistle sound, not perform well.

C. Boat-Direction Detection Performance

Our boat-direction detection provides 100% of accuracy because it is easy to check two consecutive boat-stop piers and then the direction is decided. There is no false positive in boat-stop detection so it can guarantee that there will be no mistake in boat-direction detection. Although it is easy to achieve 100% accuracy, the challenge of designing this detection module is to improve speed of detection. As mentioned earlier, the direction is a required information for boat arrival time prediction so the faster the direction is known, the faster the arrival time can be predicted.

In case that the passenger embarks at the first pier, the direction is known instantly. Otherwise, the time spent for the boat-direction detection is solely based on the boat-stop detection accuracy. To be precise, it depends on the accuracy

of detecting the second boat-stop pier. If the second boat-stop pier is missed, more time is used to detect the direction. Since the boat-stop detection performance is good as shown in the section IV.B, the boat-direction detection can certainly detect the direction once the second boat-stop pier is detected.

D. Boat Classification Performance

To classify boat type, a sequence of the boat-stop piers is needed. And the accuracy of boat classification depends on the sequence of the boat-stop piers. In our experimental result, the accuracy of the boat-stop detection is high, so the boat classification never misclassifies the boat type. Another metric that should be considered is the time spent for classification. The boat classification needs more time to process than the boat-direction detection because it requires sequence of multiple boat-stop piers whereas the boat-direction detection requires a sequence of only two boat-stop piers. Table 1 summarizes the maximum number of piers that is needed until our system can classify the boat type.

E. Boat Arrival Time Prediction Results

When we recorded the data, we also collected the GPS location for benchmark the arrival time of our system. We compare our predicted time with the real boat arrival time. Figure 9 shows that the result is very accurate. Specifically the error is less than one minute for the first next pier. The error margin is wider according to the distance of the pier. The error in arrival time is higher in further pier because it accumulates the error from the piers before. Though, at the fifth pier the mean error time is still less than 4 minutes.

TABLE 1. MAXIMUM PIER USED FOR CLASSIFIED EACH BOAT TYPE

Boat Type	Orange	Gray	Green	Yellow
Maximum number of piers used	5	5	4	4

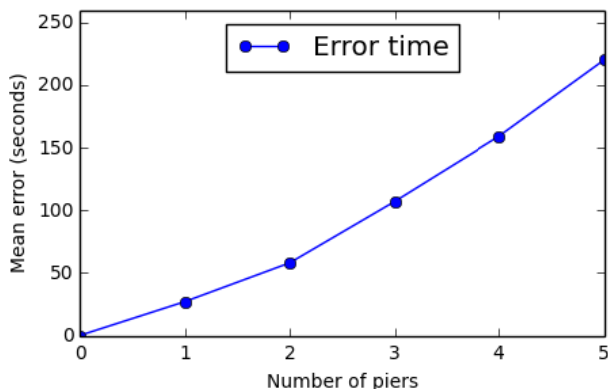


Fig. 9. Mean error in boat arrival time prediction

V. CONCLUSION

To the best of our knowledge, the proposed system in this paper is the very first boat arrival time prediction system. To predict the arrival time, only the sensors in mobile are used. No additional infrastructure is needed on boat or pier. Moreover, the system does not require users to input anything to their mobile phones. At the same time, the system does not use GPS, which consumes high power. Instead, the system utilizes energy-efficient sensors, which is perfect for the boat environment and can save battery. Our system, albeit effortless and energy-efficient, performance is yet comparable with bus arrival time prediction, which was introduced many years ago. We have done experiment on our prototype system with Chao Phraya Express Boat in Bangkok, Thailand. The results show that our system can predict the arrival time accurately.

ACKNOWLEDGMENT

This project has been supported by Special Task Force for Activating Research (STAR) Funding in Wireless Network and Future Internet Research Group, Chulalongkorn University.

REFERENCES

- [1] Transport Statistics Sub-Division, Planning Division, Thailand. http://apps.dlt.go.th/statistics_web/statistics.html
- [2] Chao Phraya Express Boat Website, Thailand. <http://www.chaophrayaexpressboat.com/en/home/>
- [3] S. G. U. Ionut Constandache (Duke), Matt Saylor (Duke), Romit Roy Choudhury (Duke), Landon Cox (Duke), "EnLoc: Energy-Efficient Localization for Mobile Phones," IEEE INFOCOM 2009.
- [4] J. Biagioni, T. Gerlich, T. Merrifield, and J. Eriksson, "EasyTracker: automatic transit tracking, mapping, and arrival time prediction using smartphones," presented at the Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems, Seattle, Washington, 2011.
- [5] A. Thiagarajan, J. Biagioni, T. Gerlich, and J. Eriksson, "Cooperative transit tracking using smart-phones," presented at the Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems, 2010.
- [6] R. K. Balan, K. X. Nguyen, and L. Jiang, "Real-time trip information service for a large taxi fleet," presented at the Proceedings of the 9th international conference on Mobile systems, applications, and services, Bethesda, Maryland, USA, 2011.
- [7] J. Z. Aaron Steinfeld, Anthony Tomasic, Daisy Yoo, Rafae Dar Aziz, "Mobile transit information from universal design and crowdsourcing," Transportation Research Record: Journal of the Transportation Research Board, vol. 2217, pp. 95–102, 2
- [8] P. Zhou, Y. Zheng, and M. Li, "How long to wait?: predicting bus arrival time with mobile phone based participatory sensing," presented at the Proceedings of the 10th international conference on Mobile systems, applications, and services, Low Wood Bay, Lake District, UK, 2012.
- [9] M. A. Y. Moustafa Youssef, Mohamed El-Derini, "GAC: Energy-Efficient Hybrid GPS-Accelerometer-Compass GSM Localization," Globecom 2010
- [10] J. Paek, K.-H. Kim, J. P. Singh, and R. Govindan, "Energy-efficient positioning for smartphones using Cell-ID sequence matching," presented at the Proceedings of the 9th international conference on Mobile systems, applications, and services, Maryland, USA, 2011.
- [11] I. Constandache, X. Bao, M. Azizyan, and R. R. Choudhury, "Did you see Bob?: human localization using mobile phones," presented at the Proceedings of the sixteenth annual international conference on Mobile computing and networking, Chicago, Illinois, USA, 2010.
- [12] H. Lu, W. Pan, N. D. Lane, T. Choudhury, and A. T. Campbell, "SoundSense: scalable sound sensing for people-centric applications on mobile phones," presented at the Proceedings of the 7th international conference on Mobile systems, applications, and services, Poland, 2009