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Bluetooth based Face-to-Face Proximity Estimation on Smart Mobile

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Abstract
The availability of "always-on" communications has tremendous implications for a way individuals move socially. Above all, sociologists have an interest within the question if such pervasive access will increase or decreases face-to-face interactions. In contrast to triangulation that seeks to exactly outline position, the question of face-to-face interaction reduces to at least one of proximity, i.e., square measure the people inside a particular distance? What is more, the matter of proximity estimation is sophisticated by the very fact that the measuring should be quite precise (1-1.5 m) and might cover a large kind of environments. Existing approaches like GPS and Wi-Fi triangulation square measure insufficient to fulfill the wants of accuracy and adaptability. In distinction, Bluetooth, that is often obtainable on most smartphones, provides a compelling different for proximity estimation. During this paper, we have a tendency to demonstrate through experimental studies the effectiveness of Bluetooth for this precise purpose..

Keywords: *Communications, face-to-face, smartphones, bluetooth*

INTRODUCTION
Overview
The traditional laptop computer to completely fledged smartphones has introduced inexpensive, always-on network property to important swaths of society. Network applications designed for communication and property offer the ability for individuals to achieve anyplace at any time within the mobile network cloth. Data communication like texting and social networking, connect people and communities with ever increasing info flows, all the whereas changing into additional more interlinking. There are a unit compelling analysis queries whether or not such digital social interactions area unit modifying the character and frequency of human social interactions. A key metric for sociologists is whether or not these networks facilitate face-to-face interactions, i.e., area unit 2 or a lot of people at intervals an exact distance that would afford such interactions? Interactions aren't restricted to any explicit space and may occur at a large sort of locations, starting from sitting and chatting during a Starbucks eating house whether or not these networks impede face-to-face interactions. Studies have shown that aggregation occurrences of communications supported self-reporting, wherever subjects area unit asked concerning their social interaction proximity, is unreliable since the accuracy depends upon the regency and saliency of the interactions With the increasing convenience of information in logs generated by smartphones, there are a unit tremendous opportunities for aggregation information mechanically.

The crucial technical challenge is the way to live face-to-face interactions, walking and chatting across a school field. As are going to be explored later within the paper, for many face-to-face interactions, the approximate distance between people in casual language is at intervals 0.5 to 2.5 meters

EXISTING SYSTEM

Wi-Fi triangulation can present a reasonable degree of accuracy, its accuracy in all but the most dense Wi-Fi deployments is insufficient, ranging on the order of 3 to 30 meters. Similarly, cell phone triangulation suffers from an even worse accuracy Moreover, while Wi-Fi is reasonably pervasive, Wi-Fi tends to generally be sparser in green spaces, i.e., outdoor spaces.

Notably, GPS suffers from both an accuracy shortcoming (5-50 m) as well as a lack of viability indoors. It is important to note that face-to-face interaction does not demand an absolute position as offered by the previously mentioned schemes but rather requires a determination of proximity. With that important shift of the problem definition, Bluetooth emerges as a straightforward and plausible alternative, offering both accuracy (1-1.2 m) appropriate smoothing and consideration of a wide variety of typical environments.

PROPOSED SYSTEM

Advance of Proposed System

We explore the energy potency and accuracy of Bluetooth compared with Wi-Fi and GPS via real-life measurements. We have a tendency to deploy associate application “PhoneMonitor” that collects information like Bluetooth RSSI values on 196 Android-based phones. Supported the info assortment platform, we have a tendency to are able to use the proximity estimation model across many real-world cases to supply high correct determination of face-to-face interaction distance.

We have a tendency to study the link between the worth of Blue-tooth RSSI and distance supported empirical measurements and compare the results with the theoretical results victimisation the radio propagation model.

SYSTEM ARCHITECTURE

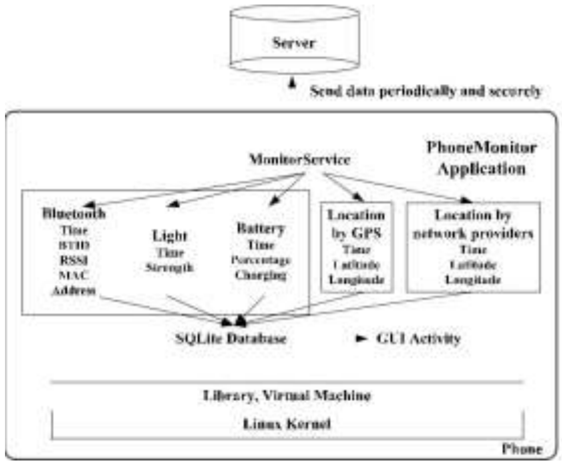

Fig. 1: *System Architecture.*

MODULE DESCRIPTIONS

Data Collection System

Phone Monitor collects Bluetooth knowledge as well as the elaborate values of RSSI, macintosh address, and Bluetooth identifier (BTID). The info is recorded in sd card once the phone detects alternative Bluetooth devices around. Additionally to Bluetooth, knowledge points from a range of alternative subsystems (light device, battery level and etc.) are gathered so as to check and improve the proximity estimation.

Power Comparison

Energy is one in every of the foremost necessary concerns for applications on smartphones. Compared to a laptop, the energy of mobile phones is sort of restricted. So it is essential to utilize an energy saving methodology within the system. Before we tend to reveal the link between Bluetooth RSSI values and therefore the distance. There are 3 ways to live the energy consumption on the smartphone. One is to use a model introduced in Android 2.0 to check the battery each application is taking. However, the numbers are normalized and it does not pro-vide the detailed power measurement. Another way is battery simulator such as Monsoon. Such expensive way measures the accurate power usage but it goes far beyond our requirement. The third way to measure energy consumption is to write an app to log the battery level and export the log to computer for analysis.

Proximity Estimation Model

Smart phones cannot predict phone orientation, antenna style is usually optimized to account for this truth. Second, though we tend to placed 2 phones on either side of a cubicle board, such an appointment failed to have an effect on RSSI considerably. Third, the foremost vital environmental issue came from the backpack. It should be as a result of the signal of Bluetooth is disturbed or protected in such a closed setting. Carry their phone in a very purse or backpack (particularly on a university campus), the backpack setting bears any investigation.

Light Sensor Data

The Blue-tooth RSSI values are much smaller than the indoor ones when the phone is in the backpack or outdoors. One of our observations is that it is possible to treat the light sensor data as an indicator of the environment. the light sensor data distribution in different settings: during the daytime when the phone is inside the building the light sensor returns values between 225 to 1,280; while this value comes up to larger than 1,280 when phone is under day-light. When the phone is in the backpack, the light values are typically around 10. Therefore, when the light sensor value is in a range that indicates the phone is in a specific corresponding environment.

FUTURE ENHANCEMENT

In the future, we tend to will improve our threshold algorithms with data processing. The thresholds employed in the proximity estimation model square measure supported the experiment results on Nexus S 4G phones. For various phones, such thresholds are also totally different. Therefore, a lot of general technique is important to see the connection between Bluetooth RSSI values and therefore the face-to-face proximity. With a lot of information according within the next following 2 years, a lot of economical data processing algorithmic rule is required to research the info. Throughout the nighttime, solely the info according by lightweight sensing element isn't reliable. One attainable technique to unravel this drawback is to require air pressure into thought to see whether or not the phone is indoor or out of doors.

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