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A Context-Aware Social Distancing Nudge for Public Health in Response to COVID-19 Pandemic

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Abstract. The impact of COVID-19 pandemic to our society may be unprecedented. While an effective cure or vaccine is under development, maintaining social distance is an essential step in defending personal as well as public health. This study conceptualizes the social distance nudge, while developing and validating a choice architecture that aims to influence and modify users' behavior in maintaining social distance for self-interest. Data concerning distance calibration was collected, and a nudging simulation was conducted in August 2020. Future work will consider including environment sensor data to improve nudging accuracy and behavioral studies to better understand user experience.

Keywords: Coronavirus, COVID-19, Nudge theory, Social distance nudge, Bluetooth, RSSI, public health, voluntary contact tracing.

1 Introduction

COVID-19 pandemic has seriously disrupted the lives of individuals across the globe with devastating effect. To date, it has claimed countless lives worldwide, with the United States reporting the highest death rate [1]. Public health faces a difficult battle on multiple fronts; healthcare protocols are complex, economies are in flux, unemployment expanding, education systems straining to fulfill their functions, and an air of uncertainty settles across the populace. These notable obstacles, taken separately, are significant in their own right. Together they present a titanic problem. Although COVID-19 is not the first in a history of pandemics (e.g., Black Death in 1347-1351, Spanish flu in 1918, SARS in 2002-2004, Ebola outbreak in West Africa in 2014-2016), the challenge that COVID-19 has brought to the present society is unprecedented, which has caused the society to re-structure in response to this threat.

Both the public and private sector are committed to reducing the impact of COVID-19, and to restoring society to pre-pandemic times. However, without a vaccine or a cure, the future of society remains uncertain [2]. Sablik and Schwartzman [3] state that the economic impacts caused by COVID-19 pandemic will be prolonged far beyond the 2006-09 housing crisis based on the soaring figures of unemployment and the sharply drop of GDP growth. The effects of COVID-19 have the potential to persist well beyond its tenure as a pandemic.

Although numerous approaches have been studied in an attempt to stem active cases, at the time of this writing, response options to COVID-19 are still limited [4] to preventative strategies such as wearing masks, social distancing, quarantine and sanitation of surfaces [2]. In the absence of effective Coronavirus treatments, social distancing is deemed as a critical preventative approach to protect one's self [5]. Social distancing refers to "keeping a safe space between yourself and other people who are not from your household" [5]. As we actively seek solutions to protect individuals and the community as a whole, our research question arises naturally: *Can a social distancing nudging concept be developed as a theory and as a practice*? [6] *How do we computationally "nudge" individuals when they are dynamically approached by others*?

This article is outlined as follows. Section two provides literature reviews of related work in nudge theory and Bluetooth technology. Section three describes the study framework of our research. Section four delineates the experiments, with nudge concept validation, and findings. Section five concludes the study and sets out future work.

2 Related Works

In this section, we first review nudge theory and its applications. Then, we discuss the groundwork and the current status of RSSI-received signal strength in Bluetooth technology.

2.1 Nudge Theory

Nudge Theory was brought to prominence by Thaler and Sunstein [7]. This concept of nudging is part of behavioral economics which emphasizes the psychological aspect of individual decisions. The work explores how individuals are largely affected by many factors in their environment which are nonobtrusive. The framework is created in order to better understand and analyze many different mechanisms, referred to as '*nudges*,' which can affect an individual's ultimate decisions. The work is largely promoted by libertarian paternalists because they believe that individuals can be '*nudged*' without restricting their choices. This is an enabling mechanism to persuade individuals to make better decisions of their own accord, without forceful intervention or extreme measures. This fulfills the goals of influencing and modifying behavior while respecting individual choice. The model is designed as an influencer, the choice architecture, and in which it interacts with and influences users when making decisions. The assertion is that the choice architecture is able to provide a context in which the individual is better enabled to make decisions for self-benefit.

The nudge theory is commonly applied in economic policy areas [8] as well as financial context [9]. Sugden [8] highlighted the application of occupational pension plans in behavioral economics. Individuals can be 'nudged' to save more money and make substantial contributions to their wealth. Sabbaghi [9] also emphasized the effects of nudges that can influence an individual's choice to borrow responsibly and lead healthier lives. Apparently, the technology sector is no stranger to using subtle mechanisms to affect user choice. Abouzied and Chen [10] illustrated a use of a technological implementation of a nudge in order to create a more social environment for users. The authors identified the problem of social interaction in urban areas where social norms discourage interaction and distant the self from strangers. In order to remove the interaction barrier, a simple technology '*nudge*' (a context-aware profile matching system), was implemented to encourage social interaction while maintaining user privacy. Moreover, Wang, Leon, et al. [11], [12] designed modifications to the Facebook web interface that 'nudges' users to consider privacy implications before online disclosures. Their study reported that while some users found these privacy nudges helpful, others found them unnecessary or overly intrusive.

Another application worth mentioning is the use of mobile devices for managing personal health. Binns and Low [13] drew attention to nudges in public health and health promotion. The use of a 'gentle nudge' to encourage healthy behaviors can contribute to the goal of public health, which is to 'deliver health to all" [13]. Martens [14] emphasized that public health can be more effective when changes and measures can occur "downstream (individual clinical or curative), midstream (education and promotion) and upstream (healthy public policy and built environment) (p. 2)." Our study aims towards influencing individual measures, by identifying a suitable application that takes data from the device's sensors and Bluetooth connected devices, and "nudges" users with social distancing context-awareness information. By providing users with context-aware information, we believe the nudge action can better inform users of the state of their surroundings. Mapping to nudge theory [7], the choice architecture in our study is the system that can better observe social distancing measures and provide contextual information to the users through the data offered by a mobile device.

2.2 RSSI Signal Strength and Bluetooth Technology

Bluetooth technology has been studied and applied in many different areas, and Received Signal Strength Indication (RSSI) has become a popular as a rudimentary approach for measuring distance. Ionescu, de la Osa, et al. [15], for example, used Bluetooth technology to track objects and find their locations. Bluetooth beacons were used to estimate distances between mobile devices and associated objects. Specifically, the study attached StickNFind beacons to objects which send signal every 100 milliseconds when paired with the smartphone, using the RSSI value of the Bluetooth signal to calculate distance. Multiple measurements were adopted, and the results demonstrated an improvement of the distance estimation with Kalman filter, which provides a better estimate of the mean, and adds more stability to signal strength.

Chowdhury, Rahman, et al. [16], on the other hand, proposed a multi-step approach to measure and approximate the distance from RSSI for BLE (Bluetooth Low Energy) devices. That is, they combined the Linear Approximation Model (LAM[1]), the Free Space Friis Model (FSFM[2]) and the Flat Earth Model (FEM[3]), with the low cost RSSI smoothing algorithm. The results minimized the dynamic fluctuation of radio signals received from each reference device when the target device is in motion, and was able

[1] RSSI values great than –44 dBm.
[2] RSSI values between –53 and –44 dBm.
[3] RSSI values less than –53 dBm.

to reduce errors when measuring distance. Given the lack of accuracy in distance estimation through empirical evaluation in RSSI-based state of the art techniques, Palaghias, Hoseinitabatabaei, et al. [17] developed a new machine learning-based solution to measure smartphone users' interpersonal distance and relative orientation. The collaborative sensing scheme allowed the detection and exchange of the facing direction information between users. Their study provided for high accuracy when detecting the interpersonal interactions in a real-world environment.

Regarding the COVID-19 context, Google [18] & Apple [19] collectively introduced a protocol for privacy-preserving contact tracing, which allows app developers to build applications that can find interpersonal contact events so that a user can be alerted if one of his contacts become COVID positive.

Leith and Farrell [20] reported challenge to measuring the BLE-received signal strength for proximity detection, which can vary substantially depending on the relative orientation of handsets, as well as absorption by the human body and reflection/absorption of radio signals in different locations such as buildings and trains. More studies are needed in terms of quantifying the error rates of proximity detection methods using BLE-received signal strength.

3 The Study

Our research team developed a CV19 SelfDefense[4] android mobile phone app [21] with an embedded feature called the "social distance nudge."

3.1 Design of the Choice Architecture

The architectural design of the choice architecture—the social distance nudge—is illustrated in **Fig. *1***. Users first activate the automated scan service on the app. A background service is spawned periodically to check and search for nearby devices every X minutes (X is configurable). We use RSSI value of Bluetooth signals received from other devices to estimate the distance to other devices.

Based on the inverse-square law[5], the signal strength will decrease as the physical distance increases. We use this concept to estimate the distance. As RSSI is measured in decibels, dBm, on a logarithmic scale and is negative. A more negative number indicates the device is farther away. For example, a value of –20 to –30 dBm indicates that the device is closer than a value of –120 dBm.

Getting RSSI value of a Bluetooth signal in an Android device is relatively easy. The Android OS provides the method to get RSSI value of Bluetooth signal starting from API level 21[6]. The full range of RSSI value[7] is [–127, 126] dBm. Social distancing is

[4] CV19 SelfDefense mobile app free download at https://isensoranalytics.com

[5] Inverse-square law: https://en.wikipedia.org/wiki/Inverse-square_law

[6] Android codenames, tags and build numbers: https://source.android.com/setup/start/build-numbers

[7] Android developer guide for get RSSI: https://developer.android.com/reference/android/bluetooth/le/ScanResult#getRssi()

recommended by CDC guidelines[8] to be at least 6 feet. In our initial estimate, if any device comes within that 6 feet range, the app generates the notification and completes the nudging process.

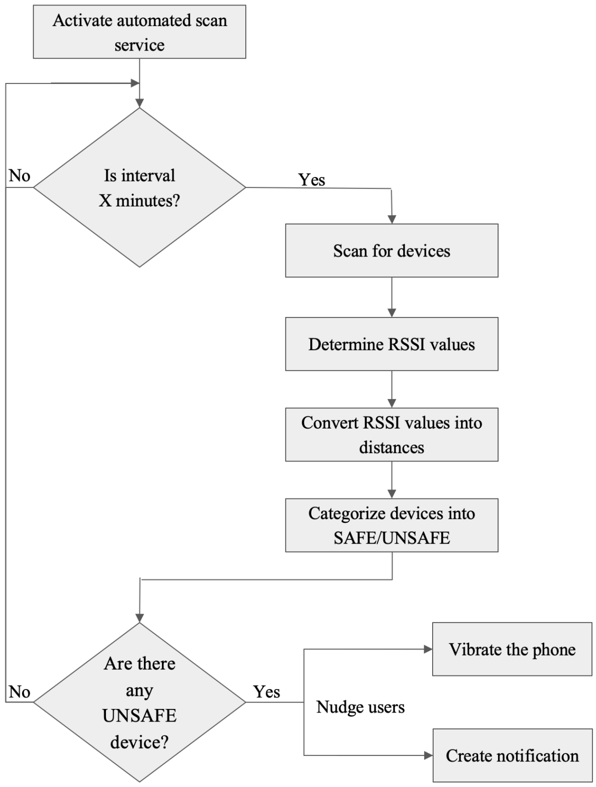

Fig. 1. Architectural design of social distance nudge.

Below we discuss the experiments performed on distance calibration, as well as simulations of social distance nudging.

4 Experiments

Two experiments on the social distance nudge were conducted, and data was collected in August 2020.

4.1 Experiment 1: Distance Calibration

The first experiment was to understand Bluetooth signal strength with relation to physical distance. Table 1 describes the parameters used for the distance calibration.

[8] CDC Guidelines for social distancing: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html

Table 2 illustrates the measurements of RSSI values when mapped to the physical distance.

Table 1. Configuration settings for experiment 1

Originator device	Oppo F7 (Android Pie)
Receiver device	Oppo F9 (Android Pie)
Position of the participants	Standing and holding the phone
Environment	Indoor and outdoor

Table 2. Mapping of RSSI Values to Distance (collected in August 2020)

Distance	Environment				
	No.	Outdoor		Indoor	
		RSSI	Mean RSSI	RSSI	Mean RSSI
2ft	1	–50	–50	–39	–38.75
	2	–48		–45	
	3	–52		–35	
	4	–50		–36	
4ft	1	–57	–56	–45	–47
	2	–55		–46	
	3	–54		–46	
	4	–58		–51	
6ft	1	–65	–65.25	–65	–54
	2	–63		–51	
	3	–65		–51	
	4	–68		–49	
8ft	1	–68	–66.5	–53	–59.5
	2	–66		–66	
	3	–66		–61	
	4	–66		–58	
10ft	1	–69	–67.25	–62	–63.75
	2	–70		–63	
	3	–65		–66	
	4	–66		–64	

Based on this data collection, it is evident that the signal strength decreases in accordance with incremental physical distance. We confirm that the values of signal strength for indoor settings are not the same as for outdoor settings. In indoor settings, the difference between the mean RSSI value of 6ft and 8ft is approximately 5.5 whereas in the outdoor settings the difference is only about 1.25. As RSSI values tend to fluctuate, it is not easy to draw a conclusive line.

4.2 Experiment 2: Simulation of Social Distance Nudge

The second experiment was purposed to validate the social distance nudge concept. In this experiment, we simulated the automated scanning process, and then observed the time lags of social distance nudging. Table 3 describes the parameters used for a social distance nudge simulation. Table 4 illustrates the indoor measurements of nudges whereas Table 5 illustrates the outdoor measurements of nudges.

Table 3. Configuration settings for experiment 2

Originator device	Oppo F7 (Android Pie)
Receiver device	iPhone 11 iOS 13.6.1
Scanning interval	60 seconds
Position of the participants	Sitting and holding the phone
Outdoor RSSI threshold	–65 dBm
Indoor RSSI threshold	–55 dBm

Table 4. Nudge simulation in indoor settings (collected on 08/26/2020)

Distance	Indoor				
	No.	Start time	Nudge time	Time lag (secs)	Nudge notification
3ft	1	1:30:03	1:31:29	86s	Unsafe
	2	1:35:59	1:38:25	146s	Unsafe
	3	1:39:38	1:43:06	208s	Unsafe
5ft	1	1:59:20	2:00:49	89s	Unsafe
	2	2:01:47	2:03:14	87s	Unsafe
	3	2:03:58	2:07:30	212s	Unsafe
6ft	1	1:53:20	-	-	Safe
	2	1:55:25	-	-	Safe
	3	1:57:26	-	-	Safe
7ft	1	2:08:26	2:09:52	86s	Unsafe
	2	2:10:35	2:12:03	88s	Unsafe
	3	2:12:48	2:14:16	88s	Unsafe
10ft	1	2:15:24	2:16:55	91s	Unsafe
	2	2:21:25	-	-	Safe
	3	2:24:50	-	-	Safe

Table 5. Nudge simulation in outdoor settings (collected on 08/28/2020)

Distance	Outdoor				
	No.	Start time	Nudge time	Time lag (secs)	Nudge notification
3ft	1	3:41:13	3:43:20	127s	Unsafe
	2	3:44:32	3:46:00	88s	Unsafe
	3	3:47:42	3:49:11	89s	Unsafe
5ft	1	3:50:47	3:52:22	95s	Unsafe
	2	3:53:17	3:56:00	163s	Unsafe
	3	3:57:05	3:58:32	87s	Unsafe
6ft	1	3:59:23	4:00:50	87s	Unsafe
	2	4:01:49	4:03:20	91s	Unsafe
	3	4:03:58	4:06:30	152s	Unsafe
7ft	1	4:07:18	4:09:02	104s	Unsafe
	2	4:09:46	4:11:14	88s	Unsafe
	3	4:12:15	4:13:52	97s	Unsafe
10ft	1	4:15:05	-	-	Safe
	2	4:19:11	-	-	Safe
	3	4:21:46	-	-	Safe

The RSSI threshold value for indoor was set to –55 whereas the RSSI threshold for outdoor was set to –65 (Table 3). This means that any mobile device sending signals with an RSSI value great than –55 (indoor) or –65 (outdoor) would be declared an "unsafe" distance, whereas any mobile device with less than –55 (indoor) or –65 (outdoor) would be declared a "safe" distance. Data in Table 4 validates the social distance nudge concept in an indoor setting, and the RSSI estimation works well within a 5-foot distance. Anytime the auto scan was activated, the phone would vibrate with a notification alert that an "unsafe" device was approaching. However, false positives sometimes occur at 6 to 7 feet. Data in Table 5 also validates the social distance nudge concept in an outdoor setting. Nonetheless, a vibration occurs at 7 feet distance with the notification of "unsafe" in both indoor and outdoor settings. Apparently, this was caused by the fluctuations of RSSI signal strength values in an indoor environment. As the RSSI signal strength fluctuates, it is impossible to estimate distance with total accuracy. Other sensor data should be considered for future work to allow for a more accurate estimation of physical distance.

5 Conclusion and Future Work

The paper not only conceptualizes the social distancing nudge based on 'Nudge theory' [7], but also describes a computational prototype for 'nudging' based on RSSI signal strengths. The choice architecture designed as the 'social distance nudge' was developed to influence and modify user behavior. By calculating the RSSI signal strength between mobile phones, a nudge is generated as a gentle reminder to the users in social distancing. 'Social distance nudging" is an explicit component of the 'Nudge theory' which provides a clear role to influence users to consciously maintain appropriate social distance. The 'social distance nudge' can dynamically construct the context by sensing users' surroundings and providing context-aware information that enables users to make choices in their own self-interest.

In this choice architecture model, the goal is to have individuals become more aware and inclined to practice social distancing. In this study, the definitions of Nudge theory are adapted to a software context. This software model is therefore likened to policy-making, but moreover providing dynamic contextual inputs to the users. In addition, disclosure on users' surroundings is controlled by the users, and thus elevates users' right to information privacy. Moreover, as privacy is a major concern for contact tracing apps across the globe [22], this approach bolsters users' control over personal contact information. Release of information would require users' voluntary consent, and thus illustrates the potential for the voluntary contact tracing for public health.

Future work requires that the 'choice architecture' design be brought to functionality in a user context. An advanced user behavioral study is required to understand users' experience and adoption of the 'social distance nudge.' A crucial question to ask would be: Does the user's behavior change because of an effective nudge? Discovering whether the nudge is effective or not will provide data for further iterations of the application to improve its performance, or even to redesign it from that start. Kosters and Van der Heijden [6] made some distinctions in evaluating of the effects of nudges. Within the software context much more data can be collected for the evaluation process due to the nature of mobile devices to log report usage data. There can be experiments that are external to the user such as observing their behavior within a constructed context or also include surveys in which users communicate their own conscious decisionmaking process. The next area for exploration is the confirmed functionalities as used by the nudge. The application uses Bluetooth signal strength as a measure of distance, meaning that aspects of the application related to Bluetooth—such as how the scanning is performed, data organization and communication, and accuracy tuning of the SAFE/UNSAFE ranges—should be further measured and validated so that the intended effects are as expected. Further work should emphasize both software validation and behavioral impact on the individuals as well as collectively on the community for public health.

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