A Risk-sensitive Social Distance Recommendation System via Bluetooth Towards the COVID-19 Private Safety

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Abstract

In this paper, we study a risk-sensitive social distance recommendation system to ensure private safety from COVID-19. Thus, we formulated a social distance recommendation problem by characterizing Conditional Value-at-Risk (CVaR) for a personal area network (PAN) via Bluetooth beacon. Further, we solve the formulated problem by proposing a two phases algorithm based on a linear normal model. In the first phase, we estimate the distance between a person and all available other users in PAN, which also categorizes into high, moderate, and safe users. Meanwhile, we execute a linear normal model to find the recommended distances for the person's private safety with a tail-risk measurement in the second phase. Finally, experiment results show the efficacy of the proposed solution approach in terms of environmental factors for the Bluetooth beacon, and risk measurement for the distance recommendation for private safety.

1. Introduction

Nowadays, the outbreak of COVID-19 is a global crisis that can prevent by maintaining a certain social distance among the peoples [1]. Therefore, communication technologies are the prominent candidates to ensure that social distance by measuring distance, analyzing risk, and recommending a private safety distance from the others. Especially, the Internet of Things (IoT) technologies [2] already anticipates such distance measurement and recommendation issues for smart city [3], green IoT network [4], cellular network [5], and so on. In fact, Bluetooth is one of the key technologies [2] that can measure distance between two IoT devices in close proximity for both indoor and outdoor environments in a personal area network (PAN). Further, the benefit of using Bluetooth beacon includes frequency hopping spread spectrum (FHSS) technique that can reduce interference between other wireless technologies. Therefore, the Bluetooth spectrum usages a range between 2.402 and 2.480 GHz, or 2.400 and 2.4835 GHz including guard bands 2 MHz wide. As a result, received signal strength indicator (RSSI) can effectively measure the distance between a person and others by activating Bluetooth based PAN. On the other hand, conditional value-at-risk (CVaR) [4], [6] is one of the effective risk measurement metrics that can cope with a tail-risk from the distribution for the measured distance in PAN.

In this paper, we focus to develop a risk-sensitive social distance recommendation system via Bluetooth beacon to assure private safety from the epidemic risk of COVID-19. The summary of the contributions are as follows:

- First, we formulate a risk-sensitive social distance recommendation problem, which can cope with a tail-risk of the recommended social distance for private safety.
- Second, we solve the formulated problem by designing a linear normal model and propose a two phases algorithm to achieve the goal of private safety from the spread of COVID-19. Further, the proposed algorithm can discretize into high risk, moderate risk, and safe range based on distance.
- Finally, our experimental analysis shows that the proposed model can efficiently recommend safe movement distances for a person in PAN and reaches 45.11% of risk for 95% CVaR-confidence.

This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government(MSIT) (No.2019-0-01287, Evolvable Deep Learning Model Generation Platform for Edge Computing). *Dr. CS Hong is the corresponding author.

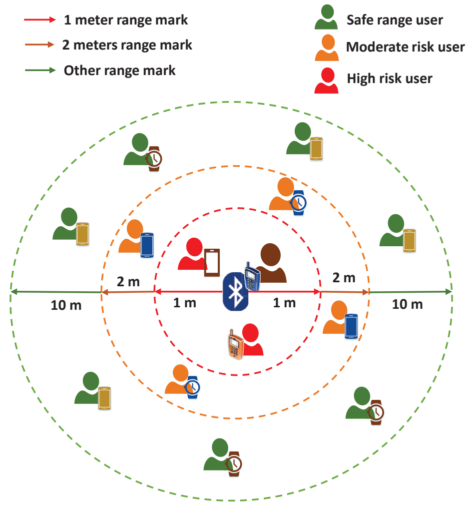

Figure 1: System model.

2. System Model and Problem Formulation

We consider a bluetooth enabled personal area network (PAN), where one person u can transmit power p [dBm] to a set $\mathcal{K} = \{1, 2, \dots, K\}$ of K nearby IoT device users. The person u then receives RSSI r_k signal from each user k. Thus, we can estimates a distance h_k between person u to a user k as follows [2]:

$$h_k = 10^{(\theta - r_k)/(10\phi)}, \tag{1}$$

where $\theta = -69$ dBm denotes measured power, and ϕ is a constant value that depends on the environmental factors (i.e., range of ϕ in $2-4$). In this system model, the users

Algorithm 1: Risk-sensitive Safe Movement Social Distance Recommendation based on Linear Model

Input: $r_k \in \forall\mathcal{K}$, θ, ϕ, α
Output: $\boldsymbol{a}, \forall\mathcal{K}$
Initialization: θ, ϕ, α, T, t, $l_k \in \forall\mathcal{K}$, $\boldsymbol{h}, \forall\mathcal{K}$, ξ

1: **for Until:** $t \geq T$ **do**
2: **Phase 1:** Distance calculation and data preparation
3: **for** $\forall k \in \mathcal{K}$ **do**
4: **Calculate:** $h_k \in \mathcal{K}$ using (1)
5: **Label:** $l_k \in \mathcal{K}$ using (2)
6: **Append:** h_k to $\boldsymbol{h}$
7: **end for**
8: **Phase 2:** Movable safety distance recommendation
9: **for Until:** $P(\Upsilon(\boldsymbol{a},\boldsymbol{h})) \geq \xi_\alpha(\boldsymbol{a})$ **do**
10: $\sigma, \mu = volatility * \sqrt{\frac{1}{K}}$
11: $\xi_\alpha(\boldsymbol{a}) = norm.ppf(1-\alpha) * \sigma - \mu$ for (5)
12: $\Phi_\alpha(\boldsymbol{a}) = \frac{1}{(1-\alpha)} * norm.pdf(\xi_\alpha(\boldsymbol{a})) * \sigma - \mu$ for (6)
13: **Calculate:** $H_\alpha(\boldsymbol{a}, \xi)$ for (7)
14: **end for**
15: **Send recommendation to** u**:** $\boldsymbol{a}, \forall\mathcal{K}$, $l_k \in \mathcal{K}$
16: $t = t + 200$ ms
17: **end for**
18: **return**

Table I: Summary of experimental setup

Description	Value
Significance probability level α	$[0.1, 0.05, 0.01]$ [4]
Environmental factors ϕ	$[2, 3, 4]$ [2]
Measured power θ	-69 dBm [2]
No. of other users K	$[1, 102953]$ [7]
Each broadcast period t	200 ms [7]

are categorized into three categories based on a distance h_k [meter] from the person u to each user k, as shown in Figure 1. Thus, the range is labeled as follows:

$$l_k = \begin{cases} 0, \text{ if } h_k \leq 1, \\ 1, \text{ if } h_k > 1 \;\&\; h_k \leq 2, \\ 2, \quad\quad \text{otherwise}, \end{cases} \tag{2}$$

where $l_k = 0$, $l_k = 1$, and $l_k = 2$ if each user k stay in high risk area (i.e., with in 1 meter), moderate risk area (i.e., 1 to 2 meter), and safe range are (i.e., more than 2 meters distance), respectively, for the person u. We define a safe distance v_k [meter] for the person u from a user k. Further, we consider a safe movement function $\Upsilon(\boldsymbol{a}, \boldsymbol{h})$, where the movement of the person u associated with a decision vector $\boldsymbol{a} \in \mathbb{R}^1$. That determines the distance is needed to move for the person u in a safe place. A set of decision vectors $\boldsymbol{a} \subset \mathbb{R}^1$ denotes the available movement options for the person u such that $\boldsymbol{a} \in \boldsymbol{\mathcal{A}}$. Considering a random vector $\boldsymbol{h} \in \mathbb{R}^1$ that stands for uncertainties of each other users k (i.e., current distance h_k). Therefore, the safe movement distance for a person u is defined as follows:

$$\Upsilon(\boldsymbol{a}, \boldsymbol{h}) = \min_{\boldsymbol{a} \in \boldsymbol{\mathcal{A}}} \mathbb{E}_{d_k \sim \boldsymbol{h}} \big[\sum_{k \in \mathcal{K}} (v_k - h_k) \big]. \tag{3}$$

In (3), for each $\boldsymbol{a} \in \mathbb{R}^1$, a safe movement distance $\Upsilon(\boldsymbol{a}, \boldsymbol{h})$ is a random variable that distance relies on a probability distribution of $P(\boldsymbol{h})$. We consider a given CVaR confidence level ξ, where a probability distribution of $\Upsilon(\boldsymbol{a}, \boldsymbol{h})$ is denoted by $\psi(\boldsymbol{a}, \xi)$. Thus, $\psi(\boldsymbol{a}, \xi)$ satisfies the CVaR confidence ξ (i.e., cutoff point), while the safe movement distance $\Upsilon(\boldsymbol{a}, \boldsymbol{h})$ is inversely proportional to CVaR confidence ξ. Thus, for a fixed safe distance $\boldsymbol{a}$, a cumulative distribution for a function of ξ is defined as follows [6]:

$$\psi(\boldsymbol{a}, \xi) = \int_{\Upsilon(\boldsymbol{a},\boldsymbol{h}) \leq \xi} P(\boldsymbol{h}) d\boldsymbol{h}, \tag{4}$$

where $\psi(\boldsymbol{a}, \xi)$ is nondecreasing with respect to ξ and we consider that $\psi(\boldsymbol{a}, \xi)$ is a continuous function [6] with respect to ξ. For any significance probability level $\alpha \in (0, 1)$, the value-at-risk (VaR) $\xi_\alpha(\boldsymbol{a})$ and CVaR $\Phi_\alpha(\boldsymbol{a})$ are related with the random variable $\boldsymbol{a}$. Therefore, a VaR $\xi_\alpha(\boldsymbol{a})$ is defined by,

$$\xi_\alpha(\boldsymbol{a}) = \min_{\xi \in \mathbb{R}} \psi(\boldsymbol{a}, \xi) \geq \alpha, \tag{5}$$

where $\xi_\alpha(\boldsymbol{a})$ determines a value ξ such that $\psi(\boldsymbol{a}, \xi) = \alpha$. Then the conditional value-at-risk $\Phi_\alpha(\boldsymbol{a})$ is defined as follows:

$$\Phi_\alpha(\boldsymbol{a}) = \min_{\xi \in \mathbb{R}} \frac{1}{(1-\alpha)} \int_{\Upsilon(\boldsymbol{a},\boldsymbol{h}) \geq \xi_\alpha(\boldsymbol{a})} \Upsilon(\boldsymbol{a}, \boldsymbol{h}) P(\boldsymbol{h}) d\boldsymbol{h}, \tag{6}$$

where the probability $P(\Upsilon(\boldsymbol{a}, \boldsymbol{h})) \geq \xi_\alpha(\boldsymbol{a})$ is equal to $1-\alpha$. Therefore, $\Phi_\alpha(\boldsymbol{a})$ is the conditional expectation while a safe movement distance is also associated with the random variable $\boldsymbol{a}$. Here, to ensure private safety for person u, he/she needs to move at least $\xi_\alpha(\boldsymbol{a})$ distance (i.e., cut-off point). Thus, to characterize the $\Phi_\alpha(\boldsymbol{a})$ and $\xi_\alpha(\boldsymbol{a})$, we formulate risk-sensitive social distance recommendation problem as follows:

$$H_\alpha(\boldsymbol{a}, \xi) = \min_{\xi \in \mathbb{R}} \xi + \frac{1}{(1-\alpha)} \int_{\boldsymbol{h} \in \mathbb{R}^1} [\psi(\boldsymbol{a}, \xi) - \xi]^+ P(\boldsymbol{h}) d\boldsymbol{h}, \tag{7}$$

where $[.]^+$ is positive and as a function of ξ, $H_\alpha(\boldsymbol{a}, \xi)$ is continuous differentiable [6]. In (7), our goal is to determine movable safety distance $\boldsymbol{a}$ for a person u over the distribution of ξ in such a way that satisfies $P(\Upsilon(\boldsymbol{a}, \boldsymbol{h})) \geq \xi_\alpha(\boldsymbol{a})$. Therefore, we solve the problem (7) by applying a normal linear model. A detail discussion of the solution is given in the later section.

3. Solution Approach

We propose a two phases Algorithm 1 to solve the risk-sensitive social distance recommendation problem (7). The Algorithm 1 is executed by a smart device (e.g., smart phone or smart watch) of person u that transmits power p in PAN. Meanwhile, Algorithm 1 feeds RSSI signals $r_k \in \forall\mathcal{K}$ as an input and initialize other variables. Lines from 3 to 7 in Algorithm 1 works for phase one that calculates current distance (in line 4) and marks each users $k \in \mathcal{K}$ into a distinct user zone in line 5. Risk-aware movable safety distance is determined by Algorithm 1 from lines 10 to 13. Line 10

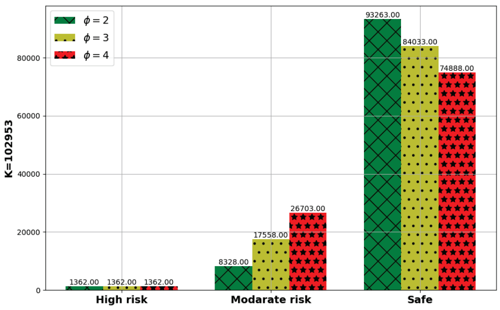

Figure 2: Distance based risk zone analysis with environmental factor ϕ from $2016-10-16$ $20:13:53$ to $2016-10-17$ $04:33:07$ for Bluetooth beacon id 80 of dataset [7].

calculates mean and variance based on the volatility of users distances $\boldsymbol{h}$. Further, lines 11 and 12 determines the Value-at-Risk and Conditional Value-at-Risk for safety distance decision $\boldsymbol{a}$. Risk-sensitive social distance recommendation is estimated by line 13 in Algorithm 1. Finally, Algorithm 1 notifies the recommendation to person's u device. The entire procedure is executed for each $t = 200$ ms that is a suitable broadcast interval for a stable Bluetooth beacons. The computational complexity of Algorithm 1 belongs to the family of $O(K^2)$ for each interval, where K is the number of devices available in PAN.

4. Experimental Result

We have implemented the proposed risk-sensitive social distance recommendation Algorithm 1 on the python platform. We have used RSSIReport dateset [7] to analyze the effectiveness of the proposed Algorithm 1. We illustrate the important parameters in Table I for the experiment setup. First, we compare risk zone detection based on the environmental factor ϕ of PAN in Figure 2. This Figure shows when ϕ is high then the moderate risk increases that describes more obstacles in the environment induces more risk toward the private safe distance. Second, we analyze private CVaR risk for a person in Figure 3. The CVaR risk of social distance for 99% and 95% CVaR-confidence achieve 60.93% and 45.11%, respectively. In other words, using 95% CVaR-confidence, we need to handle 45.11% risk for maintaining private safety distance. Finally, a comparison between VaR and CVaR for the recommended distance analysis from $2016-10-16$ $20:13:53$ to $2016-10-17$ $00:23:52$ of Bluetooth beacon id 65 in dataset [7] is shown in 4. Thus, the proposed risk-sensitive social distance recommender can provide a highly reliable safety measure to prevent the COVID-19 due to social spread.

5. Conclusion

In this work, we have introduced a risk-sensitive social distance recommendation system for ensuring private safety from the pandemic of COVID-19. We have utilized the concept of Bluetooth beacon for a PAN that can ensure a reliable distance measurement from the other user in close proximity. To do this, we formulate a risk-sensitive social distance recommendation problem by incorporated

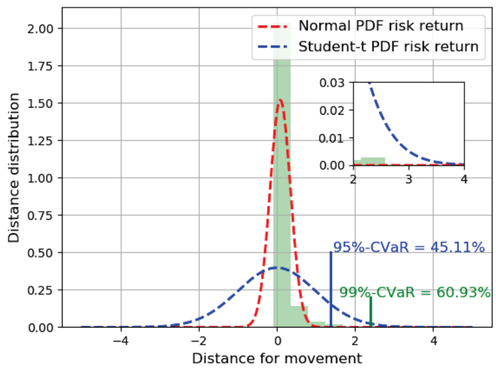

Figure 3: Private CVaR analysis for recommended distance of the Bluetooth beacon id 65 in dataset [7].

Figure 4: VaR vs. CVaR for recommended distance analysis from $2016-10-16$ $20:13:53$ to $2016-10-17$ $00:23:52$ of Bluetooth beacon id 65 in dataset [7].

Conditional Value-at-Risk that can efficiently discretize the risk of a distance movement for a person. We have solved the formulated problem in a linear model and proposed a two phases algorithm. Finally, we have performed a rigorous experimental analysis and found 45.11% risk for 95% CVaR-confidence to achieve private safety from the COVID-19. In the future, we will develop smart device applications with a more robust design mechanism.

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