Indoor mmWave Wearable Networks: Analysis of Interference and Clustering Principles

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***Abstract*—Millimeter wave (mmWave) serves as an ideal solution for wearable networks where device density can be high and many applications require Gbps throughput. In a dense scenario such as a crowded train or stadium, users are close to each other and the interference can be strong. Furthermore, wearable devices may have heterogeneous transmission capabilities and different Quality-of-Service (QoS) requirements. The wearable network in dense scenarios differs from other mmWave networks in two ways: (1) human body blockage and body movements make interferers have different interfering channels; (2) heterogeneity in device capabilities (e.g. beamforming v.s. omni-directional and different energy constraints) makes it inefficient to schedule all devices in the same way. Different scenarios poses challenges to the design of medium access control (MAC) protocols. In this paper, we begin with an analysis of the characteristics of interferers in dense wearable networks. We compute the number of strong interferers of a typical user and study the stability of strong interferers when users moves locally. We further show that when users make large scale movements, the channel state between two fixed points should be modeled as an $M/G/\infty$ queue instead of two-state Markov model. Based on our analysis of interferers, we discuss the hierarchical MAC to manage interference, including the clustering of users and scheduling at the user level. We propose clustering principles for wearables and analyze the performance of clustering and try to characterize the optimal cluster size of clusters for different scenmarios and device capabilities. We show that coexistence of heterogeneous devices present challenges and clustering and reuse can provide moderate gain in resource reuse but improves the probability of successful transmissions.**

I. Introduction

The market for wearable devices is growing fast in recent years [1] and research on wearable networks is now being actively pursued. Users are equipped with multiple wearable devices on the body with the devices of a user communicating with each other. To support the high data rates and high density of wearable devices, millimeter wave communication serves as a good solution and standards have been developed for short-range wireless personal area network (WPAN) in mmWave, e.g., 802.11ad [2], 802.15.3c [3] and ECMA387 [4].

In dense wearable network with high user density, e.g., a train car or a crowded stadium, the number of interferers is high and the existing protocols may fail to coordinate the vast number of WPANs and meet the QoS requirements of different devices efficiently due to high density of interferers and highly variable channels. The design of medium access control (MAC) for dense and heterogeneous wearable networks requires understanding of characteristics of interference environment and the requirements of different devices.

Two major factors influencing the interference environment in dense wearable networks are human blockage and user movements. Human body introduces a path loss of over 20dB [6] thus the variation in channel gain is large. [7] analyzes blockage effect in urban area and compute the penetration loss of the path using stochastic geometry tools. [8] studies the human shadowing effects in finite-sized area where the locations of users are fixed. The authors uses different path loss exponents and fading models to model the line-of-sight (LOS) and non-line-of-sight (NLOS) channels and compute the signal-to-interference-ratio (SINR) distribution. [9] compute the SINR in random networks in enclosed environment and incorporate the first order reflections from walls, the ceiling and the floor. The analysis of the interference in mmWave mainly focus on the distribution of SINR and the users are assumed to be uncoordinated, i.e., the users either transmit all the time or use simple MAC protocols like Aloha.

Another important feature of dense wearable network is that channels are more sensitive to user movements, including small local movement like turning torso or swinging and large scale movement, e.g., people walking around. Existing work on the user mobility of users [10][11][12] study the influence of human mobility on the radio channel between fixed transmitter and receiver. [10][12] present measurements on the impact of human mobility and show that human movements causes variations in channel. [12] further compute the probability that channel is blocked by users and model the state of channel using two states Markov model. [11] use simulations to get the radio propagation in the presence of static and moving obstacles and show that directional LOS wave links experience relatively high outage. These works provide valuable measurements and insights on the influence of moving human blockage, but they do not provide tractable analysis of user movements to quantify the influence of user mobility.

In dense wearable networks, the MAC protocol need to coordinate a massive number of users and improve the reuse of the resources. Many existing work on MAC design focus on improving resource reuse for centralized network where a single PNC (in 802.15.3c) or AP (in 802.11ad) coordinates the transmissions of different links [13][14][15]. Only the interference within the BSS is considered while the interference between BSSs are not considered. Furthermore, centralized MAC requires signaling overhead for measurement and control signals. In dense wearable networks, the channel between different users are unreliable and the number of devices/BSSs is large, thus existing work on centralized MAC may fail to schedule the devices. [16][17] study distributed MAC protocol for mmWave networks and use memory to improve the resource reuse of the system. However, in highly dense wearable networks, the number of potential interferers can be high and pure distributed MAC may fail to coordinate the large number of users.

802.11ad provides a distributed clustering to coordinate the BSSs. The cluster head synchronize the BSSs and schedule the beacon transmissions while the PCPs/APs schedule the data transmission within each BSS. To avoid interference, a BSS may re-schedule service periods (SPs) and contention-based access periods (CBAPs) in its beacon interval or move the beacon transmission interval in an attempt to mitigate any interference with transmission indicated in the received Extended Schedule element in the beacons of other BSSs. The BSSs work in a TDMA-like method and the resource allocated to each BSS may not be enough. Also in dense wearable networks, the channels are unstable due to human blockage and movements thus the clusters may suffer from frequent changes in cluster topology. How to select the channel and the cluster to join when multiple clusters are available is not specified, thus we propose the principles for clustering and channel selection based on our analysis of channels.

In this paper, we address the MAC design in dense indoor mmWave wearable networks. We consider the case where the user density is high and the devices on a user form a BSS coordinated by the smart phone. Due to the high density of users and unstable channels, the measurements of channel and the exchange of signaling is limited thus the MAC should rely on limited channel measurements and robust changes in network topology and we aim to propose the principles of MAC for such network.

We first provide an analysis of interference environment, specifically, we characterize the set of strong interferers a BSS might see in dense wearable networks. We model the users as a marked point process (m.p.p.) with the locations of the users following a Poisson Point Process (PPP) while the orientations of the users being the marks. We compute the spatial distribution of strong interferers and show that the number of strong interferers is actually limited as user density increases. We then analyze the influence of user movements of different scales, i.e., small local movements and large scale constant velocity movements. For small local movements, we compute the sensitivity of interferers at different distance and show that strong interferers are most sensitive when user density is moderate high, assuming that the range of local movements is limited for high user density. For large scale movements, we assume that users moves at constant velocities and analyze the channel state of a fixed link. We prove that the state of the channel follows a $M/G/\infty$ queue instead of the simple Markove model used in existing works and the distribution of intervals of being blocked has a heavy tailed distribution. We further compute the average length of intervals of being LOS/NLOS using the analytical model.

Based on our analysis of strong interferers, we argue that clustering plus MAC scheduling at BSS is an viable hierarchy for the MAC in dense wearable networks. Clustering and channel selection can be used to mitigate interference while scheduling at each user can be used to schedule wearable devices and improve channel reuse by learning the transmission patterns of other users. We propose a clustering and channel selection algorithm based on Affinity Propagation (AP) and show that the proposed algorithm can improve the stability of channels between cluster members and cluster heads and reduce inter-cluster interference.

Thirdly, we evaluate the performance of clustering and channel selection for dense wearable network with heterogeneous devices, i.e., transmission capabilities and demand of traffic, using analytical model. The members of a cluster are randomly distributed in a circle, whose dimension is decided by the cluster size, and the cluster head is located at the center of the circle. Channel selection generate a circular protection region around the cluster centered at the cluster head. The size of the protection region is decided by cluster size and the number of channels and interferers are randomly located outside of the protection region following a thinned P.P.P.. Users within the same cluster can coordinate with each other and achieve full spatial reuse while the interferers outside the cluster are not synchronized and there is no coordination among clusters. Based on the proposed model, we compute the successful transmission time (STT) for different user densities and user devices. We provide the optimal cluster size maximizing average STT for different scenarios and our results indicate that clustering and reuse provide moderate gain in STT due to reserved beacon overheads but improves the probability of successful transmission.

The rest of the paper is organized as follows. In the next section, we give the analysis of the strong interferers and how user movements affect the interference environment using stochastic geometry tools. In Section III, we discuss the clustering and channel selection principles and propose AP-based clustering algorithm. In Section IV we analyze the performance of clusters for different scenarios and characterize the optimal cluster size. Section V concludes our paper.

II. Interference in Dense Wearable Network

In highly dense wearable networks, a user has a large number of neighbors in close proximity, but there are several factors limiting the actual number of interferers a user sees at one time, including the shadowing of human body, directional transmissions and upward-downward directionality of wearable network. The factors Also, directional transmissions will limit the width of beam and a user will be interfering with fewer other users. The upward-downward directionality comes from the general posture of humans and location of common wearable devices. Many devices are located along the torso instead of around the torso thus when directional transmission is used, transmission is in upward or downward direction, reducing the probability of interfering with other users.

The exact modeling of the channels, especially the NLOS channels is still an open question and there has been quite a few works on channel modeling for mmWave, using channel modeling and/or measurements. In our analysis, we assume human body blockage will block the interference channel and we consider one time reflection over the ceiling. We ignore the reflections or scattering from human bodies or other objects.

A. Number of Strong Interferers

We first analyze the set of strong interferers seen by a typical user. Users are standing on a 2-D plane with the typical user at the origin. There is no walls or obstructions other than human body, and there is a ceiling at H. The human body is modeled as cubics as shown in Fig. figure of body model and the locations of the users follow a point process $\Phi = \{x_i\}_i$, where x_i is the location of user i, u_i, and the facing direction of user i is θ_i. Each user has a device located in front of the human body, at the height of 1m and we consider the interference seen by the device of the typical user.

The locations of devices on human body are the same and we assume the dimensions of users are the same, then the network can be modeled as a marked point process (m.p.p.) $\tilde{\Phi} = \{(x_i, \theta_i)\}_i$. Assuming the facing direction of the typical user is θ_0, the number of strong interferers is given by,

$$N_{\mathrm{SI}}(\tilde{\Phi}, \theta_0) = \sum_{(x_i,\theta_i)\in\tilde{\Phi}} f_0(x_i, \theta_i, \tilde{\Phi}\backslash\{(x_i,\theta_i)\}, \theta_0) \quad (1)$$

where $f_0(x_i, \theta_i, \tilde{\Phi}\backslash\{(x_i,\theta_i)\}, \theta_0)$ is the indicator function that whether u_i is a strong interferer of the typical user located at the origin, given the location and orientation of u_i, (x_i, θ_i), the orientation of the typical user, θ_0, and blockages from other users, $\tilde{\Phi}\backslash\{(x_i,\theta_i)\}$. f_0 is 1 if there is an LOS channel between devices or a strong unblocked reflected channel over the ceiling.

N_{SI} varies for different realizations of users, and the distribution of N_{SI} is hard to compute. The average number of strong interferers works as a good metric to understand the requirements on MAC. Assuming that $\{\theta_i\}$ are mutually independent and the distribution of θ_i depends only on the location of u_i, x_i, then $\tilde{\Phi}$ is independently marked[18]. Using the reduced Campbell's formula for i.m.p.p. [18], the expected number of strong interferers $\mathrm{E}[N_{\mathrm{SI}}]$ can be expressed as,

$$\begin{aligned}\mathrm{E}[N_{SI}] &= \mathrm{E}^0\Bigg[\int\limits_{\mathbb{R}^2\times\mathbb{R}} f_0(x_i, \theta_i, \tilde{\Phi}\backslash\{(x_i,\theta_i)\}, \theta_0)\tilde{\Phi}(\mathrm{d}(x,\theta))\Bigg] \\ &= \int\limits_{\mathbb{R}^2}\int\limits_{\mathbb{R}}\int\limits_{\tilde{\mathbb{M}}} \mathrm{E}_{\theta_0}[f_0(x,\theta,\tilde{\phi},\theta_0)]P^!_{(x,\theta)}(\tilde{\phi})F_x(\mathrm{d}\theta)M(\mathrm{d}x)\end{aligned} \quad (2)$$

where E^0 is the expectation given that there is a user at the origin, E_{θ_0} is the expectation over θ_0, $\tilde{\mathbb{M}}$ is the set of all possible realizations of $\tilde{\Phi}$, $P^!_{(x,\theta)}$ is the palm distribution of marked point process given that there is a point (x, θ) and a point at the origin. $F_x(\mathrm{d}\theta)$ is the probability measure of the orientation of the user located at x and $M(A) = \mathrm{E}[\Phi(A)]$ is the mean measure of points Φ.

For tractability, we use homogeneous Poisson Point Process to approximate the locations of users. The facing directions of users are independent of user locations and uniformly distributed in $[0, 2\pi)$. Given these assumptions, we can compute the probability that a user located at x is a strong interferer of the typical user. Let OX be the link between the centers of the typical user and the user at x and we use OX to approximate the link between user devices. Let $N_{\mathrm{B}}(x)$ be the number of users blocking the LOS channel, then

$$N_{\mathrm{B}}(x) = \sum_{(x_i,\theta_i)\in\tilde{\Phi}\backslash(x,\theta)} 1((x_i,\theta_i) \text{ blocks } OX).$$

$1((x_i, \theta_i) \text{ blocks } OX)$ is independent from other users thus the users blocking OX is a independently thinned process of $\tilde{\Phi}$ thus N_{B} follows a Poisson distribution and the probability that the OX is not blocked is $e^{\mathrm{E}[N_{\mathrm{B}}]}$. $\mathrm{E}[N_{\mathrm{B}}]$ is given by the following equation,

$$\begin{aligned}\mathrm{E}[N_{\mathrm{B}}(x)] &= \int\limits_{\mathbb{R}^2}\int\limits_{[0,2\pi)} 1((x',\theta') \text{ blocks } (x,\theta))F_{\theta'}(\mathrm{d}\theta')\lambda(\mathrm{d}x') \\ &\overset{(a)}{\approx} \int\limits_{\mathbb{R}^2}\int\limits_{[0,2\pi)} 1\big(l_x(x') < \frac{1}{2}d_{x'}(\theta'-\theta_x)\big) \\ &\quad\times 1\big(s_x(x') \in [0, |x|]\big)F_{\theta'}(\mathrm{d}\theta')\lambda(\mathrm{d}x') \quad (3) \\ &= \lambda|x|\int\limits_{\mathbb{R}}\int\limits_{[0,2\pi)} 1(d_{x'}(\theta') < 2l)\frac{\mathrm{d}\theta'}{2\pi}\mathrm{d}l \\ &= \lambda|x|\mathrm{E}[D] \quad (4)\end{aligned}$$

where (a) is an approximation of N_{B}. $l_x(x')$ is the distance between x' and OX, $d_{x'}(\theta^*)$ is the sectional width of user at x' seen at an angle of θ^*, θ_x is the angle of OX. $\mathrm{E}[D]$ is the expected sectional width of a user. With the distribution of $N_{\mathrm{B}}(x)$, $\mathrm{E}[N_{\mathrm{LOS}}]$ is given in the following equation,

$$\begin{aligned}\mathrm{E}[N_{\mathrm{LOS}}] &= P_{\text{facing}}\int\limits_{\mathbb{R}^2\backslash\mathrm{B}(0,r_{\text{min}})} 1(|x| < r_{\text{max}})e^{-\mathrm{E}[N_{\mathrm{B}}(x)]}\lambda(\mathrm{d}x) \\ &= 2\pi\lambda P_{\text{facing}}\int\limits_{\mathrm{r_{min}}}^{\mathrm{r_{max}}} e^{-\lambda\cdot\mathrm{E}[D]\cdot r}r\mathrm{d}r \\ &= \frac{2\pi P_{\text{facing}}}{\lambda\mathrm{E}[D]^2}\big(e^{-\lambda\mathrm{E}[D]r_{\min}}(\lambda\mathrm{E}[D]r_{\min}+1) \\ &\quad - e^{-\lambda\mathrm{E}[D]r_{\max}}(\lambda\mathrm{E}[D]r_{\max}+1)\big),\end{aligned} \quad (5)$$

where P_{facing} is the probability of the two users are not blocked by the bodies of the two users, $r_{\min}$ is the minimum distance between the centers of the users.

For NLOS strong interferers, the number of users blocking the channel also follows Poisson distribution. We can compute $\mathrm{E}[N_{\mathrm{B}}^{\mathrm{NLOS}}]$ in a similar way as the one we use for $\mathrm{E}[N_{\mathrm{B}}(x)]$ by substituting the first indicator function in (3) with

$$1\big(h_x(x', \theta_{x'}) > h_{\mathrm{NLOS}}(x, s_x(x'))\big),$$

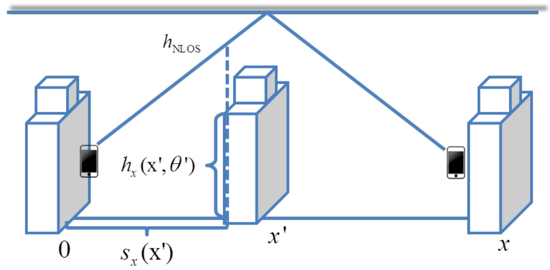


Fig. 1. User x has a clear reflected channel if there is no other user blocking the reflection path.

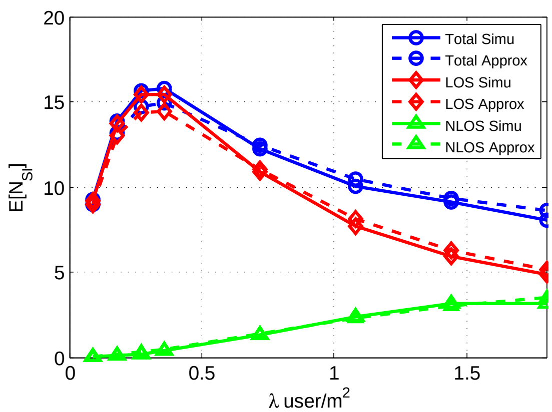


Fig. 2. $\mathrm{E}[N_{\rm SI}]$ for different user densities. Whether user at x' blocks the channel is decided by $h_x(x', \theta')$ and $h_{\rm NLOS}$.

where $h_x(x', \theta_{x'})$ is the height of blockage along OX, $h_{\rm NLOS}(x, s_x(x'))$ is the height of the reflection channel as shown in Fig. 1.

The channel gain of a clear reflected channel is influenced by path loss and the reflection coefficient of the ceiling, which is related to the incident angle, the material of ceiling and also the polarization of the incident wave. As a result, it is possible that the channel gain of NLOS channel of a close neighbor is smaller than that of a more distant user.

$\mathrm{E}[N_{\rm SI}]$ for different user densities is plotted in Fig. 2. The average number of LOS and NLOS interferers are given and the results is compared to results from simulations where the locations of users follow Matérn III process [19] instead of Poisson Point Process. Our analytical results are in line with the simulations, validating the accuracy of the approximation.

$\mathrm{E}[N_{\rm SI}]$ first grows as the user density increases. As user density further increases, users closely around the typical user forms a wall blocking the interference channels from distant interferers. Users see most strong interferers at moderate high user density, instead of high user density scenarios. Fig. illustrates how the set of strong interferers are as the user density increases, self blockage is not considered. In high density scenario, the number of users the MAC need to coordinate at the same time is actually limited, indicating that it is possible to mitigate interference in highly dense scenario using MAC to coordinate the users.

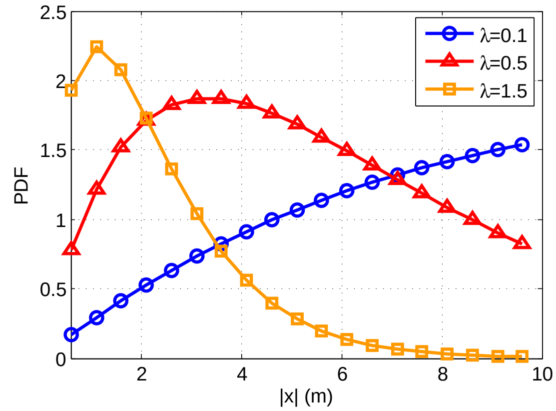


Fig. 3. Probability density function of LOS strong interferers as a function of distance to $\mathbf{0}$.

B. Sensitivity of Strong Interferers

Interference channels are sensitive to user movements, especially for dense wearable networks. The sensitivity of strong interferers defines the cost and benefit of keep tracking of and coordinating the strong interferers and how robust the strong interferers are to perturbations in the network. From t to $t+\Delta t$, the users make translations as well as rotations, the changes for the typical user and potential interferers are shown as follows:

$$(0, \theta_0) \to (\Delta x_0, \theta_0 + \Delta\theta_0)$$
$$\tilde{\Phi}_t = \{(x_i, \theta_i)\} \to \tilde{\Phi}_{t+\Delta t} = \{(x_i + \Delta x_i, \theta_i + \Delta\theta_i)\}$$

Let $Y_x^t = f_0(x, \theta, \tilde{\Phi}_t \backslash (x, \theta), \theta_0)$ be the state of an interferer located at x at time t, and $Y_x^{t+\Delta t}$ the state of the user at $t+\Delta t$ is given by,

$$Y_x^{t+\Delta t} = f_{\Delta x_0}(x + \Delta x, \theta + \Delta\theta, \tilde{\Phi}_{t+\Delta t} \backslash (x + \Delta x, \theta + \Delta\theta), \theta_0 + \Delta\theta_0),$$

$Y_x^t, Y_x^{t+\Delta t} \in \{0, 1\}$. We define the sensitivity of an interferer originally located at x, $S(x)$, as the autocorrelation of states of an interferer at t and $t + \Delta t$.

$$S(x, \Delta t) = \mathrm{Corr}(Y_x^t, Y_x^{t+\Delta t}) = \frac{\mathrm{E}[Y_x^t \cdot Y_x^{t+\Delta t}]}{\sigma_{Y_x^t} \cdot \sigma_{Y_x^{t+\Delta t}}} \quad (6)$$

Notice that the state transition of Y_x^t is not a two-state Markov process. We will explain this in detail in section II-C.

Assuming the network is stable and users movements are independent from each other, the variance of Y_x^t and $Y_x^{t+\Delta t}$ are given by,

$$\mathrm{Var}(Y_x^t) = p_{\mathrm{SI}(x)} \cdot (1 - p_{\rm SI}(x)),$$

where $p_{\rm SI} = \Pr(f_0(x, \theta, \tilde{\Phi} \backslash \{(x_i, \theta_i)\}, \theta_0) = 1)$. The sensitivity of users can be computed by computing the probability that the user remains a strong interferer after perturbation, $\Pr(\{Y_x^t = 1\} \cap \{Y_x^{t+\Delta t} = 1\})$. Define a user (x', θ') be a possible blockage if this user blocks the interference channel between the origin and (x, θ) at t at t or blocks the channel after perturbation at $t + \Delta t$. For given $(\Delta x_0, \Delta\theta_0)$

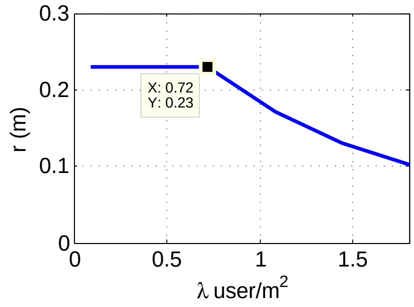


Fig. 4. Range of translation r for different user densities λ

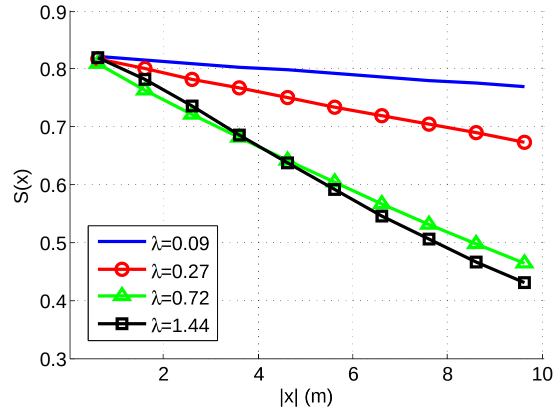


Fig. 5. Sensitivity of users at different locations.

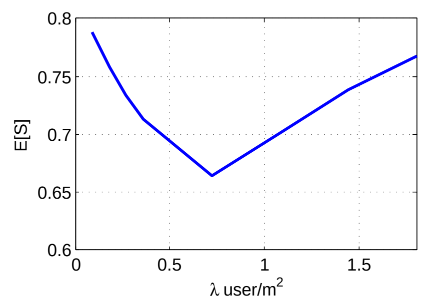


Fig. 6. $\mathrm{E}[S(x)|f_0(x_i,\theta_i,\tilde{\Phi}\backslash\{(x_i,\theta_i)\},\theta_0)=1]$ average sensitivity of strong interferers.

and $(\Delta x, \Delta\theta)$, the distribution of possible interferers follows a Poisson Point Process, thus the probability of being a strong interferer is given by

$$\Pr(\{Y_x^t = 1\} \cap \{Y_x^{t+\Delta t} = 1\} | (\Delta x_0, \Delta\theta_0), (\Delta x, \Delta\theta)) = e^{-\mathrm{E}[N_{\mathrm{PB}}(x)|(\Delta x_0,\Delta\theta_0),(\Delta x,\Delta\theta)]} \cdot \mathrm{P}^*_{\text{facing}}(\Delta\theta_0, \Delta\theta) \quad (7)$$

where $N_{\mathrm{PB}}(x)$ is the number of possible blockages, $\mathrm{P}^*_{\text{facing}}(\Delta\theta_0, \Delta\theta)$ is the probability that the interferer and the typical user are facing each other before and after perturbation.

To model the movements of users, we assume the translation of a user is uniformly distributed in a circle around the user, $\Delta x \sim \mathrm{unif}(\mathcal{B}(0, r(\Delta t)))$. $r(\Delta t)$ is the maximum range of perturbation and is related to Δt. Users also rotate by some random angle $\Delta\theta \sim \mathrm{unif}[-\omega(\Delta t), \omega(\Delta t)]$, where $\omega(\Delta t) \in [0, \pi]$ is the maximum range of rotation. When user density is moderate high, we assume the perturbation range remains the same. As user density increases, the distance between users becomes smaller and the range of translation actually becomes smaller as user density increases. The range of translation is shown in Fig. 4, while the range of rotation remains the same, $\omega = 24°$, which is $1/10$ of the angle not blocked by self-blockage.

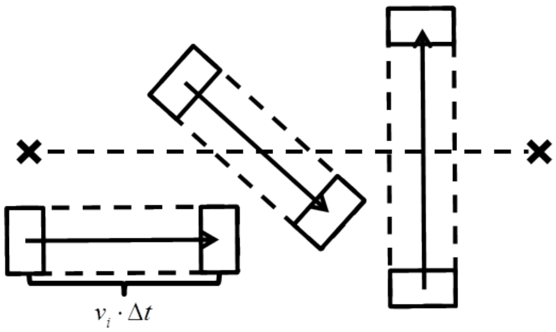
In Fig. 5, we show the sensitivity of users at different locations. Distant interferers are more sensitive to perturbations than close interferers, showing that close interferers learning the interference from close neighbors is more reliable. The sensitivity decreases as user density increases when density is low, i.e., below 0.72. As user density further increases, the sensitivity relatively stays the same as the range of movement decreases. In Fig. 6 shows how the average sensitivity of strong interferers changes for different user densities. When user density increases, strong interferers are closer while the sensitivity of users decreases, thus the average sensitivity first decrease with user density. When the range of limitation starts to decrease, the sensitivity of users remains the same while $\mathrm{E}[S]$ increases as strong interferers are closer. The above results shows that interferers are more sensitive to perturbation, and thus harder to keep track of as user density increases and the worst case happens at moderate high user density scenario, where the number of strong interferers is high and the range of perturbation is not limited by high user density.

C. Influence of Large Scale Mobility

Another scenario we are interested in is dense user environment where users moves, e.g., populated streets. For large scale mobility, we focus on the influence of human blockage and show the transition of channel states between LOS and blocked. Let OX be the channel between the target user and his neighbor x. OX is fixed while other users move towards random directions at constant speeds. We assume the initial distribution of users follows a homogeneous Poisson Point Process with density λ, the directions of users are uniformly distributed over $[0, 2pi)$ and the speed of each user x, v, is fixed. Then each user is uniquely decided by (x, v, θ). At any time t, the locations of users still follow a homogeneous Poisson Point Process with density λ.

For any time interval $[t, t+\Delta t]$, each user x will cover a rectangular area A_x as shown in Fig. II-C. OX will remain LOS if there is no user intersects with OX during the interval. The locations of users at t follows a Poisson distribution, the areas covered during Δt are independent and identically idistributed (i.i.d.), thus the coverage areas of users forms a Boolean model. For Boolean model, the number of sets that intersects with a fixed convex set follows Poisson distribution, thus the number of users blocking OX during $[t, t+\Delta t]$ follows a Poisson distribution with mean

$$\mathrm{E}[N^{\Delta t}_{blockage}] = \lambda\big(\mathrm{E}[\nu(A_0^{\Delta t})] + \frac{1}{\pi}\nu_1(OX)\mathrm{E}[\nu_1(\partial A_0^{\Delta t})]\big) \quad (8)$$



where $A_0^{\Delta t}$ is the typical coverage area for Δt, ν is the two-dimensional measure of the area, ν_1 is the one-dimensional measure, ∂A_0 is the boundary of A_0. Assuming the speed and direction of each user is constant and the shape of users are convex, then

$$\mathrm{E}[\nu(A_0^{\Delta t})] = w \cdot (d + \mathrm{E}[v]\Delta t)$$
$$\mathrm{E}[\nu_1(\partial A_0^{\Delta t})] = 2(w + d + \mathrm{E}[v]\Delta t).$$

The number of blockage during the interval follows an Poisson distribution, the users are independent from each other and the time that a user blocks OX is independent from all other users. As a result, we can model the number of users blocking OX as an $M/G/\infty$ queue. (Add a theorem or provide some proof?) The arrival rate of blockage is given by $\lambda\mathrm{E}[v](w + \frac{2|OX|}{\pi})$. The distribution of time that a user blocks OX is decided by the distribution of speed v.

Let T_{LOS} be the length of an interval that **OX** is an LOS channel and T_{NLOS} be the length of the interval that OX is blocked by at least one users. From the analysis of the $M/G/\infty$ queue, T_{LOS} follows a exponential distribution with parameter $\lambda\mathrm{E}[v](w + \frac{2|OX|}{\pi})$, then

$$\mathrm{E}[T_{LOS}] = \frac{1}{\lambda\mathrm{E}[v](w + \frac{2|OX|}{\pi})} \tag{9}$$

We can then compute the probability that OX is clear at any time t,

$$\mathrm{P}_{\mathrm{LOS}} = e^{-\mathrm{E}[N^0_{blockage}]} \tag{10}$$

where

$$\mathrm{E}[N^0_{blockage}] = \lambda\big(wd + \frac{2|OX|}{\pi}(w + d)\big)$$

is the expected number of users overlapping with OX. Notice that here we do not consider the fact that the typical user and receiver will not overlap with blockages, thus $\mathrm{E}[N^0_{blockage}]$ is a different approximation from the result in (4).

From queuing theory,

$$\frac{\mathrm{E}[T_{\mathrm{LOS}}]}{\mathrm{E}[T_{\mathrm{LOS}}] + \mathrm{E}[T_{\mathrm{NLOS}}]} = \mathrm{P}_{\mathrm{LOS}} \tag{11}$$

$$\mathrm{E}[T_{\mathrm{NLOS}}] = \frac{1 - \mathrm{P}_{\mathrm{LOS}}}{\mathrm{P}_{\mathrm{LOS}}}\mathrm{E}[T_{\mathrm{LOS}}] \tag{12}$$

Our analysis show that the state of OX is not a simple Markov process with only two states but a $M/G/\infty$ queue. The distribution of the time that OX is blocked shows heavy tailed distribution, indicating that $\mathrm{E}[T_{\mathrm{NLOS}}]$ can be very long. In some cases, the channel between two links can be blocked for a long time. For general indoor communications, this shows that outage due to blockage of 60 GHz communication can be worse than the result in analytical model. For dense wearable networks, long T_{NLOS} will result in reorganization of the users, thus the frequency of changing topology can be higher than that in Markov model.

III. Clustering and Channel Selection in Dense Wearable Networks

IV. Analysis of Clustering

V. Conclusion

VI. Simulation Evaluation

VII. Conclusion

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