Indoor mmWave Wearable Networks: Challenges to MAC Design

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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 LOS and NLOS channels and compute the SINR distribution. [9] model the wearable network in enclosed environment and the reflected channels are considered to compute the signal-to-interference-ratio (SINR) distribution of channels. The analysis of the interference in mmWave mainly focus on the distribution of SINR and assume the users are uncoordinated. Users either transmit all the time or use simple MAC protocols, e.g., 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 further consider one time reflection over the ceiling. We ignore the intractable reflection or scattered interference channels in our analysis.

A. Number of Strong Interferers

We try to analyze the set of strong interferers seen by a typical user. The typical user is located at the origin of a 2-D plane, with all the other users standing on the plane. 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. The PCP device is located in front of the human body, at the height of 1m and the facing direction of user i is θ_i.

The interferers are determined by the location and orientation of the users and the other users can be modeled using a marked point process (m.p.p.) $\tilde{\Phi} = \{(x_i, \theta_i)\}_i$. For a typical user located at the origin facing direction θ_0, the number of strong interferers given $\tilde{\Phi}$ is as follows,

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

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, considering the locations and orientations of u_i, (x_i, θ_i), the orientation of the typical user, θ_0, and blockages from other users, $\tilde{\Phi} \backslash \{(x_i, \theta_i)\}$.

For LOS interferers, f_0 is 1 if the distance between devices is close enough and the interfering channel is not blocked by the typical user, the interferer and other interferers. For NLOS strong interferers, e.g., interferer with a strong reflection over the ceiling, we need to consider human body blockage, channel path loss as well as the reflection.

N_{SI} varies for different scenarios and the its distribution is hard to compute. The average number of strong interferers works as a good metric to understand the requirements on MAC. If we assume that the orientations of users are mutually independent, then the interferers form an independent marked point process. Using the Campbell-Mecke theorem, the expected number of strong interferers $\mathrm{E}[N_{\mathrm{SI}}]$ can be expressed as,

$$\mathrm{E}[N_{SI}] = \mathrm{E}^0\left[\int_{\mathbb{R}^2 \times \mathbb{R}} f_0(x_i, \theta_i, \tilde{\Phi} \backslash \{(x_i, \theta_i)\}, \theta_0) \tilde{\Phi}(\mathrm{d}(x, \theta)) \right]$$
$$= \int_{\mathbb{R}^2} \int_{\mathbb{R}} \int_{\tilde{\mathbb{M}}} \mathrm{E}_{\theta_0}[f_0(x, \theta, \tilde{\phi}, \theta_0)] P^!_{(x, \theta)}(\tilde{\phi}) F_x(\theta) M(x)$$

(2)

where E^0 is the expectation given that there is a user at the origin, E_{θ_0} is taking the expectation over θ_0, $P^!_{(x,\theta)}$ is the

palm distribution of marked point process given that there is a point (x, θ) and a point at the origin. $F_x(\theta)$ is the CDF function of orientation for a user located at x and $M(x)$ is the CDF function that a user is located at x.

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, the number of users that may block the interference channel follows Poisson distribution and the expected number of strong interferers, $\mathrm{E}[N_{\mathrm{SI}}]$, is shown as follows,

$$\mathrm{E}[N_{\mathrm{SI}}] = P_{\mathrm{facing}} \int_{\mathbb{R}^2 \backslash \mathrm{B}(0, r_{\min})} 1(|x| < R_{\max}) e^{-\mathrm{E}[N_{\mathrm{B}}(x)]} \lambda(\mathrm{d}x)$$
$$= 2\pi\lambda P_{\mathrm{facing}} \int_{r_{\min}}^{r_{\max}} e^{-\lambda \cdot \mathrm{E}[D] \cdot r} r \mathrm{d}r$$

(3)

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. $N_{\mathrm{B}}(x)$ is the number of users that blocks the interference channel from user located at x.

$$\mathrm{E}[N_{\mathrm{B}}(x)] = \int_{\mathbb{R}^2} \int_{[0, 2\pi)} 1((x', \theta') \text{ blocks } (x, \theta)) F_{\theta'}(\mathrm{d}\theta') \lambda(\mathrm{d}x')$$
$$= \lambda|x| \int_{\mathbb{R}} \int_{[0, 2\pi)} 1(d(\theta') < 2h) \mathrm{d}\theta' \mathrm{d}h$$
$$= \lambda|x|\mathrm{E}[D]$$

(4)

where h is the distance between the center of blockage to the line between the origin and x, $\mathrm{E}[D]$ is the expected width of a user that may block the channel between the origin and user x.

$\mathrm{E}[N_{\mathrm{SI}}]$ for different user densities is plotted in Fig. 1. 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. Analytical results are in line with the simulations, validating the accuracy of the analytical model.

$\mathrm{E}[N_{\mathrm{SI}}]$ 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.

B. Sensitivity of Strong Interferers

Interference channels are sensitive to user movements, especially for dense wearable networks. The sensitivity of strong
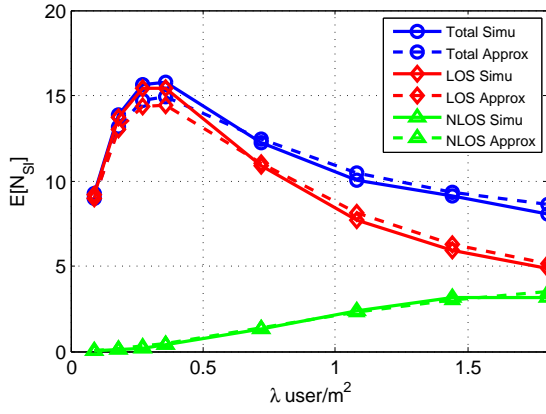
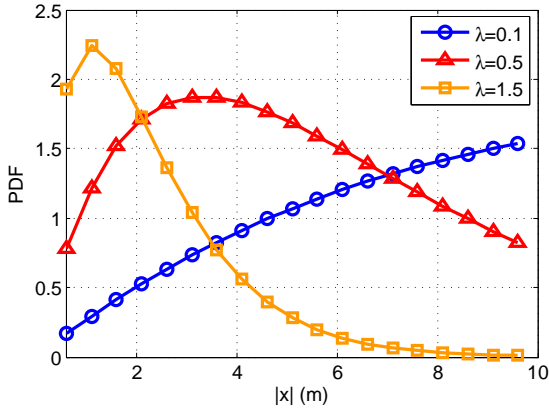Fig. 1. $E[N_{\mathrm{SI}}]$ for different user densities.

Fig. 2. Probability density function of LOS strong interferers as a function of distance to $\mathbf{0}$.

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:

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

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,

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

We define the sensitivity of an interferer originally located at x, $S(x)$, as the autocorrelation of states of an interferer at t and $t+\Delta t$.

$$S(x, \Delta t) = \mathrm{Corr}(Y_x^t, Y_x^{t+\Delta t}) = \frac{E[Y_x^t \cdot Y_x^{t+\Delta t}]}{\sigma_{Y_x^t} \cdot \sigma_{Y_x^{t+\Delta t}}} \quad (5)$$

Notice that the state transition is not a Markovian process. We will explain this in detail in section II-C.
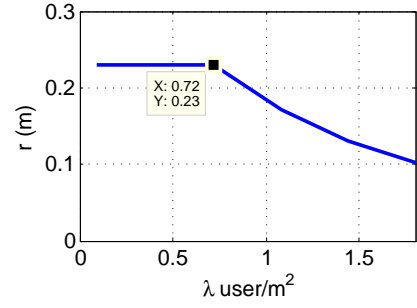

Fig. 3. Range of translation r for different user densities λ

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,

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

where $p_{\mathrm{SI}} = \Pr(f_0(x, \theta, \tilde{\Phi} \backslash \{(x_i, \theta_i)\}, \theta_0) = 1)$. 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 $(\Delta x_0, \Delta\theta_0)$ 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

$$\Pr(\{Y_x^t = 1\} \cap \{Y_x^{t+\Delta t} = 1\} | (\Delta x_0, \Delta\theta_0), (\Delta x, \Delta\theta)) =$$
$$e^{-E[N_{\mathrm{PB}}(x) | (\Delta x_0, \Delta\theta_0), (\Delta x, \Delta\theta)]} \cdot P_{\mathrm{facing}}^*(\Delta\theta_0, \Delta\theta) \quad (6)$$

where $N_{\mathrm{PB}}(x)$ is the number of possible blockages, $P_{\mathrm{facing}}^*(\Delta\theta_0, \Delta\theta)$ 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. 3, while the range of rotation remains the same, $\omega = 24°$, which is $1/10$ of the angle not blocked by self-blockage.

In Fig. 4, 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. 5 shows how the average sensitivity of
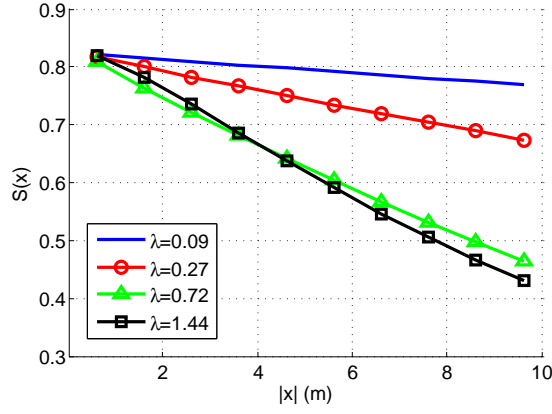
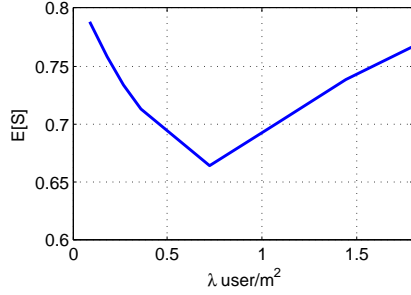Fig. 4. Sensitivity of users at different locations.

Fig. 5. $\text{E}[S(x)|f_0(x_i, \theta_i, \tilde{\Phi}\backslash\{(x_i, \theta_i)\}, \theta_0) = 1]$ average sensitivity of strong interferers.

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 $\text{E}[S]$ 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. **??**. 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

$$\text{E}[N_{blockage}^{\Delta t}] = \lambda\big(\text{E}[\nu(A_0^{\Delta t})] + \frac{1}{\pi}\nu_1(OX)\text{E}[\nu_1(\partial A_0^{\Delta t})]\big) \quad (7)$$

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

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

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 $\lambda\text{E}[v](w + \frac{2|OX|}{\pi})$. 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 $\lambda\text{E}[v](w + \frac{2|OX|}{\pi})$, then

$$\text{E}[T_{LOS}] = \frac{1}{\lambda\text{E}[v](w + \frac{2|OX|}{\pi})} \quad (8)$$

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

$$\text{P}_{\text{LOS}} = e^{-\text{E}[N_{blockage}^0]} \quad (9)$$

where

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

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 $\text{E}[N_{blockage}^0]$ is a different approximation from the result in (4).

From queuing theory,

$$\frac{\text{E}[T_{\text{LOS}}]}{\text{E}[T_{\text{LOS}}] + \text{E}[T_{\text{NLOS}}]} = \text{P}_{\text{LOS}} \quad (10)$$

$$\text{E}[T_{\text{NLOS}}] = \frac{1 - \text{P}_{\text{LOS}}}{\text{P}_{\text{LOS}}}\text{E}[T_{\text{LOS}}] \quad (11)$$

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 $E[T_{\text{NLOS}}]$ 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.

VI. Clustering and Channel Selection

Clustering improves spatial reuse and reduce interference [2]. Cluster head synchronizes the cluster members and schedules beacon transmissions in the cluster to mitigate intra-cluster interference, while other techniques like channel selection (FDM) and back off [20] can be used to reduce inter-cluster interference. The 802.11ad Standard provides both distributed clustering and centralized clustering methods for directional devices working on mmWave. The links between PCPs/APs are unstable in dense wearable networks, thus the distributed clustering method fits better and we will use the distributed clustering algorithm in 802.11ad as the baseline.

In the distributed clustering algorithm, the formation of cluster follows a first come first serve rule: a BSS tries to join a existing cluster when it enters a network and starts a new cluster if no existing cluster is available. The maintenance of clusters is similar to lowest ID clustering. If the original cluster head is lost or two clusters meet each other, the remaining BSS or the original cluster head with the lowest/lower ID will be selected as the new cluster head. The Beacon SPs of cluster members are non-overlapping in time and a BSS need to reserve the slots if the PCP/AP or other devices receive beacons or Extended Schedule element from other BSSs. Distributed clustering help schedule beacon transmissions and the BSSs share the channel in a pure TDMA way.

In dense wearable networks, the TDMA like scheduling method based on omni-directional beacons will not allocate enough resource for BSSs and channel reuse is necessary. Furthermore, the channels between devices, especially the channels between PCPs/APs of cluster members and PCPs/APs of cluster heads, are unstable, leading to frequent lost of cluster heads and reforming of clusters. A good clustering should cluster BSSs that have stable connections to cluster heads and facilitate resource reuse at BSS level.

The requirements of clustering are affected by the network scenario. If users move a lot, e.g., users getting off a subway train car or moving along the aisle, the channels changes fast and the basic requirements of clustering algorithm is to be fast in formation and maintenance. If users moves locally and are relatively stable, clusters can be optimized to form more stable clusters so that BSSs can better schedule their transmissions by learning their interference environment.

Choosing the proper size of clusters is important for dense wearable networks. Big clusters can reduce inter-cluster interference but a cluster would reserve more slots for beacon transmission and the slots for each BSS's primary high-end transmission is limited. Furthermore, the connections between cluster members and cluster heads can be unstable. Small clusters provide enough resource for each cluster member and are easy to maintain but suffer from more inter-cluster interference.

Another question with wearable network clustering is what devices should participate in clustering. Devices of the same BSS are controlled by PCP/AP and communicate with each other thus BSS is the basic unit in clustering. However,

the interference environments of different devices can be completely different due to the short wave length and human body shadowing. Choosing the devices to participate in clustering requires the trade-off between the accuracy of channel estimation and the cost for measurement and signaling. The PCPs/APs send beacons in every slot and PCPs/APs within the same cluster are required to listen to the beacons thus the channel between PCPs/APs are measured in every frame. The non-PCP/non-AP devices can measure the channel from PCPs/APs by listening to the beacons, but the measurements cost energy and the measurements need to be sent to PCP/AP. The measurement of channels from non-PCPs/non-APs will require additional pilots. In our case, the connectivity between cluster members and cluster heads require measurements and message exchange between PCPs/APs thus PCPs/APs are necessary in clustering. The high-end non-PCP/non-AP devices can measure the interfering channel from other PCPs/APs and send the results to PCP/AP to improve clustering. Low-end devices have limited energy thus they are not required to measure interference. Optimization of clusters also requires the measurements and exchange of control messages between BSSs working on different channels thus BSSs need to measure other channels and exchange messages periodically.

Our purpose here is to devise a clustering algorithm to provide stable clusters where the connections between cluster heads and cluster members are more stable and use a channel selection algorithm to further reduce inter-cluster interference.

A. Clustering based on Affinity Propagation

Affinity Propagation (AP) [21] is a distributed clustering algorithm which elects a set of exemplars and assign nodes to exemplars based on message exchange between nodes . AP clustering maximizes the sum of pairwise similarities between nodes and their exemplars, where similarity $s(i,k)$ indicates how well node k serves as the exemplar of node i. The clustering result does not depend on the initialization of cluster heads and only requires exchange of real value messages between data nodes and AP clustering can produce good clustering result at low computational and signaling cost compared to other clustering techniques such as k-centers clustering.

In AP clustering, nodes exchange two types of messages and the messages are combined to decide cluster heads and association. Each node i sends 'responsibility' $r(i,k)$ to candidate cluster head k, indicating how suitable node k works as node i's cluster head compared to other candidate cluster heads. The candidate cluster head k sends 'availability' $a(i,k)$ to node i to show the accumulative support for being a cluster head that node k receives from nodes other than i. The messages are initialized to be 0 and messages of the same type are updated at the same time.

The responsibilities are computed as the similarity minus the maximum of the sum of availability and similarity of other competing cluster heads,

$$r(i,k) = s(i,k) - \max_{k' \text{s.t.} k' \neq k} \{a(i,k') + s(i,k')\}. \quad (12)$$

The candidate cluster heads compete for the ownership of node i and the candidate cluster head with larger similarity value compared to other potential cluster heads is more likely to own node i. For $i = k$,

$$r(i,i) = s(i,i) - \max_{k \text{s.t.} k \neq i} \{a(i,k) + s(i,k)\}$$

is the self-responsibility for becoming a cluster head and $s(i,i)$ is the prior preference for being a cluster head. A negative self-responsibility means the node is better working as a cluster member instead of a cluster head. If $s(i,i)$ is large, BSS i will tend to start its own cluster and the density of cluster heads will increase; otherwise, the clustering algorithm will produce fewer cluster heads and larger clusters.

The availabilities are computed at the candidate cluster heads by adding self-responsibility and the positive responsibilities they receive from other nodes:

$$a(i,k) = \min\left\{0, r(k,k) + \sum_{i' \text{s.t.} i' \neq i,k} \max\{0, r(i',k)\}\right\} \quad (13)$$

$$a(k,k) = \sum_{i' \text{s.t.} i' \neq k} \max\{0, r(i',k)\} \quad (14)$$

A candidate cluster head with stronger support from other nodes and high self-responsibility is more likely to become a cluster head and the availability is high.

At any stage, the messages can be combined to decide the cluster heads. The nodes which have positive sum of self-availability and self-responsibility will be elected as cluster heads, i.e., $CH = \{k|a(k,k) + r(k,k) > 0\}$. Other nodes select the cluster head which maximize the sum of availability and responsibility:

$$ch(i) = \arg\max_{k \in CH} \{a(i,k) + r(i,k)\}, \forall i \notin CH.$$

However, there is no guarantee of convergence for AP clustering. To avoid numerical oscillations and reach convergence, the messages need to be damped when updated, e.g., $m(t+1) = (1-\lambda)m(t) + \lambda m$.

AP-based clustering algorithms have been proposed to produce stable clusters [22] or reduce signaling overhead[23]. In our case, we want cluster members to have stable connections to cluster heads and reduce inter-cluster interference. The stability of channels is inferred by tracking the channel quality over time. To get stable channels between users, a good 'similarity' metric would be the 'stability' of channel and we use the average channel strength to measure stability,

$$Stability(i,j) = Pr(|H_{i,j}|^2 > \gamma),$$

where $H_{i,j}$ is the record of estimations of channel gain from PCP j to PCP i in previous frames. To mitigate inter-cluster interference and facilitate the exchange of messages within cluster, cluster members should share similar strong interferers with the cluster head so that inter-cluster interference can be effectively reduced by making neighbor clusters work on different channels. We devise a metric to measure the similarity in strong interfering neighbors, *Common Neighbor*

Stability (CNS). CNS between two BSSs is defined as the sum of minimum of the two BSSs' stability to their common interfering neighbors, i.e.,

$$CNS(i,j) = \sum_{k \in N_i} \min(Stability(i,k), Stability(j,k)).$$
(15)

N_i is the set of most stable strong interferers of BSS i, $|N_i| = M$. BSS i broadcasts N_i and corresponding $Stability(i,:)$ in its beacons or clustering messages periodically and BSSs hearing the beacons update their CNS to BSS i. CNS is computed locally at each BSS and the set N varies for different BSSs thus CNS can be asymmetric, i.e., $CNS(i,j) \neq CNS(j,i)$. $Stability(i,i) = 1$ by default. We use CNS as the similarity metric for AP clustering to elect the exemplars and when a BSS decides to join a cluster, it selects the cluster head which has best stability and CNS, i.e.,

$$CH(i) = \arg\max_k \{Stability(i,k) \cdot CNS(i,k)\}.$$

Running AP clustering for a network consisting of N BSSs has a signaling complexity of $O(N^2)$. However, the actual signaling cost can be reduced to $O(N)$. Only positive responsibilities are needed thus a node only need to broadcast positive responsibilities in its beacons. For availabilities, node k just need to broadcast $a(:,k) = r(k,k) + \sum_{i' \text{s.t.} i' \neq k} \max\{0, r(i',k)\}$ to other nodes, and node i can update $a(i,k)$ as $a(i,k) = \min(0, a(:,k) - \max(0, r(i,j)))$. Furthermore, we do not need to assign non-overlapping slots for signaling: if two BSSs can hear each other, they will reserve slots for the beacon transmission of each other; if two BSSs do not have a good connection, then they are not likely to become the cluster head of the other BSS and the message exchange is not necessary. Applying AP clustering only requires each BSS to broadcast limited messages in their beacons thus the signaling over head is limited.

We use channel selection to reduce inter-cluster interference. Channel selection is performed by the cluster head to avoid using the same channel as its stable strong interferers. The PCP/AP of cluster head estimates the channels to nodes outside the cluster periodically. If the inter-cluster interference is high, the cluster head may switch to another channel with certain probability. The cluster head then estimates the interference environment on the new channel for some slots and decide to stay on the new channel or switch back to the original one based on measurements. If the network is stable, such channel selection method can assign neighboring clusters to different channels and reduce inter-cluster interference.

B. Analysis of Clustering Performance

The major variant in our clustering algorithm is cluster size. In dense wearable networks, small clusters provides more parallelism across clusters but users experience more inter-cluster interference; large clusters reduce inter-cluster interference but the resource reserved for each user is limited and the it is more difficult to maintain connections between cluster heads and cluster members. In this part we analyze the throughput of users for different network scenarios and assumptions about users and try to identify the optimal cluster size.

To model the clusters, we assume the cluster members

C. Clustering Results

We apply AP based clustering algorithm and channel selection in dense scenario. We use Markov Contention Matrix to model the channel between different users in Section II. For comparison, we also simulate lowest ID clustering, which is a simplified version of the distributed clustering algorithm used in 802.11ad. We evaluate the performance of the clustering algorithms using two metrics, the average probability of having LOS channel with cluster heads and the average number of LOS interferers working on the same channel within the cluster and outside the cluster. The clustering results are shown in Fig. and Table We can see that AP based cluster can effectively cluster the nodes that are close in proximity (well-connected) and channel selection effectively reduce the number of LOS interferers. In fact, lowest ID clustering provides fewer strong interferers, but the cluster heads and the cluster members are not well connected thus the signaling within the cluster is hard to perform. Furthermore, the number of uncoordinated LOS interferers is not reduced (if not increased). If we only perform channel selection without clustering, the average number of total LOS interferers is also smaller, but the interference is uncoordinated and more unpredictable.

Our AP based clustering algorithm requires frames scheduled for channel measurements and message exchange for BSSs working on different channels. This will introduce extra signaling cost thus we are working on devising pure distributed clustering algorithm and channel selection only relying on message exchanging on the same channel.

VII. HIERARCHICAL MAC SCHEDULING FOR HETEROGENEOUS DEVICES

With appropriate clustering and channel selection, we can form clusters that are in close proximity. The above approach does not remove inter-cluster interference completely, but the interferers from outside the cluster are more distant away thus the set of inter-cluster interferers are less stable as shown in Fig. The interfering channel to inter-cluster interferers are likely to be blocked, making learning the transmission patterns of BSSs outside the cluster ineffective. A simple way to deal with interference is to treat interference as noise. If inter-cluster interference is strong, the BSS may consider switching to another cluster or work on another channel.

After performing channel selection, the average number of strong interferers working on the same channel would be approximately $1/M$ of the average number of total strong interferers, M being the total number of channels. Such number is relative small, however, simple TDM scheduling used in 802.11ad is not enough. In 802.11ad, a PCP/AP would reserve the slots for other BSSs if the PCP/AP or the non-PCP/non-AP devices receives the extended schedule element of other BSSs. The set of strong interferers may change fast

over time, thus the number of Extended Schedule Element a BSS receive. As a result of it, there can be much more BSSs working in the same contention group. If instead, all BSSs do not reserve resource for neighbor BSSs, interference will be unpredictable, making it hard to guarantee the QoS of transmission.

As discussed in Section **??**, high-end and low-end devices have different QoS requirements and transmission capabilities. A basic principle with the MAC design is that high-end devices should work on reserved slots. BSSs would reserve the slots for the high-end transmissions to avoid degrading the QoS. For low-end devices, or not important high-end transmissions, BSS try to reuse the slots of other BSSs' high-end transmission by first sensing the channel. Due to the energy limit of low-end devices, channel sensing may not be performed in all slots. To effectively sensing and reusing the channel, low-end devices can stay idle for some time if there is interference on the channel it try to reuse or select the slot that are more likely to be idle to work on.

To apply the MAC principle, we first model the contention relationship in dense wearable network using Markov model. The channel between two BSSs, i and j, is modeled as a discrete Markov process with two states. If there is a LOS channel, or strong reflection channel between i and j, the state of channel is 0; the state is 1 otherwise. The channel state transits in each frame and the state transition diagram is shown in Fig. The state transition rate is determined by the users density, the movement pattern of users and the length of the channel.

We begin with a toy example, optimizing the reward from scheduling secondary transmission. For a slot in which a BSS works as a secondary user, the BSS can take three actions, Transmit, Sense and Idle. The reward of a successful transmission is R_{Transmit}, and the energy cost using different states is E_{Transmit}, E_{Sense} and E_{Idle}. The corresponding state transition matrix is shown in Fig. The optimization problem can be solved as a Markov Decision Process, which optimize the discounted sum of potential gain over time. Another objective is to optimize the average reward over frames. As shown in Fig. the optimization problem involves two decisions, the number of slots to wait if the channel is sensed to be interfered and the action to take after waiting. For different decisions, the stationary distribution of states and corresponding reward over time. Let k be the number of slots that a BSS stays idle after the channel is interfered by the primary user, $k = \{0, 1, \ldots, \}$. There are three states, *Transmit*, *Idle* and *Action*. *Action* is the state that a BSS either transmit or sense the channel after staying idle. The stationary distribution of the state is as follows,

$$\pi_{Transmit} = \frac{P(0| < k+1 >)}{P(0| < k+1 >) + 2 \cdot p_{block}}$$
$$\pi_{Idle} = \frac{p_{block}}{P(0| < k+1 >) + 2 \cdot p_{block}} \qquad (16)$$
$$\pi_{Action} = \frac{p_{block}}{P(0| < k+1 >) + 2 \cdot p_{block}}$$

State *Idle* takes k frames while the other two states take one frame. Given the stationary distribution of states, we can compute the average gain over time for different combination of k and action taken after waiting. A BSS can treat each slot independently and optimize the reward from each slot. However, there is limitation with the above approach. The first problem is that the secondary users might interfere with each other thus the reward from utilizing a slot is not constant. If the BSSs try to reuse the slots aggressively, there will be more interference among the secondary users thus reducing the gain of reuse. The second limitation with the naive approach is that the QoS requirements are not fully considered. The rewards of different slots in a frame are correlated. A BSS will not always have data to transmit but may have different requirements on delay. If a BSS reuse multiple slots of a frame successfully and does not have more data to transmit, the reward from reusing a new slot will be trivial, even negative. On the other hand, if the BSS does not have enough slots, a BSS should probe/transmit more aggressively to meet the QoS requirements. The third limitation is the exact optimization requires the exact channel between primary and secondary BSSs. To deal with this problem, a BSS can adjust its decision making procedure according to the results from the channel. If a slot is constantly busy, BSS can increase the time of staying Idle; otherwise, the time of waiting can be shortened. In fact, the analytical results in Fig. supports the philosophy of adaptation: the long channels are more likely to be blocked by obstructions and interference from far away neighbors are more likely to be blocked due to the movements of users, thus the channels that are often blocked are more likely to become blocked after certain frames.

Considering the above discussed limitations, we extend the hierarchical scheduling to optimize the resource a BSS can get from reusing slots in one whole frame. Each frame consists of N slots, and there are N BSSs working in one cluster. At the beginning of each frame, the PCP/AP node broadcast Beacons to the non-PCP/non-AP nodes and the schedule for the frame is contained in the Beacon, thus a BSS need to make the scheduling decisions at the beginning of each slot based on the measurements in the previous frame and can not schedule new transmissions during the frame. For a typical BSS, the state of a frame is as follows,

$$FrameState = \{SlotState_1, SlotState_2, \ldots, SlotState_N\}.$$

$SlotState_i$ is the same as the slot state used for toy example. In our design, Slot 1 is the slot reserved for primary transmission. Ignoring inter-cluster interference, the BSS does not need to consider $SlotState_1$ in scheduling. We assume the channels between the BSS and other BSSs are independent from each other, thus the state transition diagram of each slot is the same as shown in Fig. The difference is that the reward on a slot is also influenced by the interference from other BSSs in the same cluster and the QoS requirements of the BSS. Assuming the BSSs are independent from each other and all the channels between any pair of BSSs are independent from each other and the transition for each link are identical,

then intra-cluster interference is a function of the probability that a slot schedules transmission. For the QoS requirements of BSSs, the marginal gain from reusing the slot decreases with the slots available to the BSS. Considering intra-cluster interference explicitly makes the reward influenced by the decision that the BSS makes for different states, thus the standard MDP procedure no longer works. To solve such problem, one method is update the values and decisions of different states iteratively while updating the reward of state transition over iteration. The second method is to solve the problem by brute force search over the whole state space. The problem with such approach is that the size of the state space is very large. Even we limit the number of frames that a BSS would stay idle to be a limited number, e.g., M, the size of state space is $(M+2)^N$.

The computational complexity with MDP approach is not affordable thus we need to find heuristic scheduling methods for reusing the MAC, which strike a balance between simple naive scheduling over each slot and the optimization over all the potential state space. Two major objectives of heuristic scheduling includes 1) reuse slots based on measurements of channel in previous frames without knowing the exact parameter of the channel and 2) making each BSS to have some slots to work on to meet minimum QoS requirements and achieve fairness among secondary BSSs. To serve the above two objectives, the key idea of our scheduling methods is that each BSS schedule transmissions on slots where there is no interference from primary users while keeping track of an additional slot with no interference. If the channel to the primary BSS does not change, the BSS will keep using the slot; otherwise the BSS try to reuse the alternative slot instead. The detailed scheduling algorithm is as follows.

In each slot, a BSS has the channel measurements from the previous frame. There will be some slots in which a BSS does not see interference from primary users. The BSS selects K available slots to schedule its secondary transmission and keeps track of an alternative slot in case one of the reused slots is no longer available. The BSS will always have the measurements of the slots that they schedule secondary transmission. To keep track of the alternative slot, the BSS schedule $Sense$ on one of the rest of the slots. If the slot is sensed as available, it is an alternative slot and the BSS may either keep sensing that channel or sensed that channel again after some time, based on the variability of the channel. If the BSS sees interference from the primary user, it reschedule its secondary transmission on the alternative slot and scheduling sensing on the slot which has the highest probability of having no interference from primary users among the rest of the slots. If more than one slot reused become unavailable, the BSS reschedule transmissions on the slots with highest probabilities of not having interference from primary BSSs. At the same time, the BSS schedule sensing on the other slots.

VIII. Simulation Evaluation

IX. Conclusion

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