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ORIGINAL RESEARCH

Mitigate Inter-WBAN Interference in Body-to-Body Network to Restrain Epidemic Spread

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Abstract
Rapid growth of wireless technology and machine learning fueled demand for ubiquitous healthcare service in India. This necessity is served by an emerging technology called wireless body area network (WBAN). This facilitates an individual to be aware of his health status anywhere anytime without any assistance. In case of any emergency, this network is capable to initialize other automated systems. During an epidemic, if we can early detect a susceptible individual, spread of the disease can be curbed. In our paper, early detection is achieved using multiple cooperating WBANs that leads to a network called Body-to-Body Network (BBN). We have also proposed quarantine strategies by minimizing contact between different staged WBANs based on their health status. An unsupervised learning algorithm is used to efficiently divide the area into non-overlapping clusters minimizing inter-WBAN interference. We have considered two test case scenarios based on how the WBANs are distributed in BBN architecture. OMNet++-based simulator Castalia−3.2 is used to evaluate routing protocol in BBN network. Performance of our system is assessed based on network parameters like Packet Delivery Ratio (PDR). Results ensure that our method guarantees low epidemic spread of disease in enclosed area by enhancing throughput and minimizing interference of our stable system.

Keywords Body-to-body network · K-means++ · Inter-WBAN interference · Epidemic

Introduction

The increase in older adults and patients with congenital, degenerative and other diseases, together with the medical expenses that they cause, resulted in the appearance of new technologies. Replacing the doctor with an intelligent robot is a recurring theme in science fiction, but the idea of getting medical advice via digital assistance from Alexa and Siri no longer seems impossible to achieve. Owing to their potential of significantly enhancing the applicability of the healthcare sector, wireless body area networks (WBANs) are considered to be a proactive solution in medical applications. These networks are capable of continuously monitoring and acquiring physiological data for application to healthcare, chronic disease monitoring and treatment, professional training assistance, and entertainment. Due to the immense impact of WBANs and their increasing demand, the use of these networks is expected to increase [3]. The widespread use of WBANs, which is typically defined as a three-layer communication architecture, can reduce healthcare costs significantly [15, 18].

Health data acquired by a WBAN are capable of making an individual aware of their own vital stats. During a pandemic situation, where the disease is contaminating in nature, propagating the information of one's health can provide a positive societal impact. This can also curb the spread of disease. This issue raised the invention of another network where health data from one WBAN is propagated to and through other bodies. Thus introduction of body-to-body

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(BBN) solutions to transmit each WBAN's data via its network of cooperating WBAN impacts great social benefits.

Currently, our society demands a system which can convey the health status of each individual to others. Unlike [24], we have considered a timely epidemic control model by considering an intermediate state, in order to anticipate the quarantine strategy, before reaching the infected status. This ensures that the individual as well as those who are in contact are aware of the critical consequence of being in close proximity. The individual also can take measures accordingly for being safe and quarantined. Thus real-time interactions among cooperative WBANs in a BBN network may allow every person to be considered as a good citizen to auto-prevent the spread of COVID-19 like epidemics. In this context, we consider the scenario to prevent epidemic spread in an enclosed crowded area. We assume that each person in that area is WBAN enabled. The coordinator of each WBAN participate in the BBN network in a cooperative manner. The other motivation behind BBNs is to overcome the problems of coexistence and performance degradation of closely located WBANs, by involving them in mutual interactions and cooperation [20]. These data collected by the WBANs of individuals are considered as sample inputs. Substantial success has been made in deep learning producing systems to be able to learn without explicit programmed, but by building models from the sample data collected as input. The inherent requirement for large-scale high-quality well-structured data necessitates providers to move to electronic health record. References [5, 10, 12, 22] are some the recent researches that highlights these issues in their work. The current state-of-the-art mostly discusses the inefficiency of healthcare scenario to handle epidemic control. The main issue they face is receiving health status of individuals on a timely basis. Further analysis on the data takes time. This creates a delay in decision taking. As a result the person himself is unaware of his current health condition. Moreover, to decide whether a healthy person is in a critical zone, he must be aware of his surrounding. None of the current scenarios handles these issues on a real-time basis. Further, we must also take care of the communication system because corrupted data is as bad as delayed data in these cases. Cooperative network has a promising future to deal with the situation. But, none of recent researches proposed a promising BBN network to efficiently discourage epidemic spread.

The main contributions of this paper are as follows.

- Guarantee a low epidemic spread of the disease in an enclosed area by minimizing contact between non-affected and affected WBANs. Use quarantine strategies to prevent the diffusion of the disease to the population.
- An unsupervised coloring algorithm for spectrum allocation is used for a BBN network having multiple cooperative WBANs that can effectively separate the WBANs into non-overlapping clusters. The cluster heads are responsible for efficiently transmitting data with minimal interference to their nearest authorities to ensure proper analysis of the health status.

The rest of the paper is organized as follows. "Related Work" details our state-of-the-art related to the contribution. "Framework" describes the model. "Inter-WBAN Interference Mitigation" gives an overview of Inter-WBAN Interference Mitigation scheme in this paper followed by "Performance Evaluation" that provides an insight to the performance evaluation of our model. Finally, we conclude the paper in "Conclusion".

Related Work

The authors in [23] light up the inability of our current information transfer system in healthcare scenario for epidemic control. Precise estimations for epidemic situations are not conveyed in timely and efficient manner by hospitals and health workers due to delayed conveying system. In this paper, the authors have developed a new information system called EPIC that uses Social Networks in their information system for Epidemic control to accurately describe social interactions between individuals in a community infected by a pandemic. Prediction algorithms are developed to model health conditions and social interactions of individuals, which allows to predict how epidemic diseases spread in a community. EPIC algorithm is based on the fusion of collected health information from WBANs and social information from social networks, and it articulates around three steps: (i) data collection from WBANs and social networks, (ii) data interpretation and information fusion, and (iii) epidemic prediction by authorities. Though it provides timely and accurate predictions, this algorithm did not consider priority-based sensor data transmission which is the need of any epidemic condition to control. It also handles the data inefficiently as the WBANs are non-cooperative and the quarantine strategy is solely handled by the authorities. Thus susceptible individuals ignore the epidemic threats around them. Cooperative communication is another technology that can effectively mitigate interference in dense WBAN deployment like our use case scenario. The advantage of cooperative communication lies in spatial diversity. When the transmission distance between the source and the host nodes is large, or the radio condition becomes severe, the transmission reliability and energy efficiency can be improved significantly through cooperative communication [21].

In 2013, the same authors proposed an Epidemic Source Tracing Algorithm which integrates WBANs technology for body vital signs collection with mobile phones for social interaction sensing in [24]. The authors have designed a mobile phone capability-driven hierarchical social interaction detection framework integrated with WBANs. With this framework, they have proposed a set of epidemic source tracing and control algorithms including genetic algorithm-based search and dominating set identification algorithms to effectively identify epidemic sources and inhibit epidemic spread. In some pandemics, like COVID-19 there exist an intermediate status between the susceptible and the infected status. During this phase, a person though infected, but not a carrier. He stays in this latent period for sometime before being in infected status. Unlike [24], we have considered a timely epidemic control model by considering this intermediate state, in order to anticipate the quarantine strategy, before reaching the infected status.

Moreover, anticipating the quarantine strategy is not enough to control epidemic spread. All the WBANs in a BBN network need to cooperate to transmit this information in a timely and efficient manner. Thus, a methodical inter-WBAN routing algorithm is required to effectively transmit data through the BBN architecture.

Major challenges for interference mitigation of a dense system of WBANs are the following:

- they are distributed
- they exchange no information with their neighbors
- they undergo block fading, i.e., the interference channel gain may remain constant for a slot but varies from slot to slot

Very few research work has taken place for inter-WBAN routing. Some of them are discussed as follows.

The authors in [1] proposed a multiple cluster-based hybrid security framework that supports both intra-WBAN and inter-WBAN communications. The authors have ensured secure cluster formation using electrocardiogram (EKG)-based key agreement scheme and energy is used efficiently as multiple clusters are formed. Highly dynamic and random EKG values of the human body for pairwise key generation and refreshment. Modeling inter-WBAN communications as a hierarchical structure has the advantage of local data processing, which reduces the network overhead and provides a scalable solution.

The authors in [16] proposed a dynamic resource allocation scheme where each WBAN in the network exchange information to efficiently interprets an interference region with others in a close vicinity. The nodes in this region are later allocated orthogonal sub-channels, while non-interfering nodes can transmit in the same time slot. Here, the authors have assumed a minimum interference level. As WBAN deals with critical health data, during epidemic situation this assumption becomes impractical.

The authors in [4] proposed a random incomplete coloring to achieve a fast and high spatial reuse inter-WBAN scheduling. Unlike conventional complete coloring schemes, the used scheme is not limited by the trade-off between coloring speed and spatial reuse. It can always provide fast convergence with time-complexity $O(e^{w(2 \log n)/2})$ in any spatial reuse requirement. Furthermore, it can support an increase of up to 90 percent of spatial reuse over the conventional complete coloring using chromatic $X(G)$-colors, which is known to be the optimal coloring of complete coloring. But, the strict assumptions made in this paper, such as perfect superframe synchronization, make this method unsuitable for our real-life use case.

In [9], the authors have proposed a Cooperative Energy Efficient and Priority-Based Reliable Routing Protocol with Network Coding for WBAN. In this proposal, high-priority nodes are non-cooperative and uses single hop communication with sink for data transmission. All other non-prioritized sensor nodes participate in the system as data generator and cooperative relay node forwarder. They have used enhanced Cuckoo Search Optimization Algorithm for relay node selection based on parameters such as residual energy distance between sender and sink, and path loss. Resources need to be assigned pragmatically so that data of the most critical patient reaches with utmost priority. Therefore, we have compared our work with this protocol.

The authors in [12] proposed a social group interaction power control game model. New utility and cost functions accommodate both convergence speed and quality. This work proves that only one Nash equilibrium (NE) point exists for this game model, which ensures the algorithm converges quickly. Thus it mitigates interference between WBANs.

In [22], a new coexistence mechanism is proposed to mitigate the interference between multiple WBANs. The transmission power is adjusted for each coexisting WBAN using the predicted mobility, which improves the transmission outage probability and transmission energy efficiency.

In [10], the authors have formulated the channel selection of the coexisting WBAN coordinators for interference mitigation in a time-varying environment as an exact potential game. The utility is the weighted aggregate interference. It has been shown that the channel selection (action) profile which globally minimizes the interference is a pure strategy Nash Equilibrium (NE) of the game. They have considered two distributed learning method to converge the NE. This method do not requite any information exchange among the WBANs. Our use case is a time-varying network topology where the number of active WBAN users varies. This method is unsuitable for the dynamically changing network.

An Optimal Backoff Time Interference Mitigation Algorithm (OBTIM) is proposed in [21]. This method performs rescheduling or channel switching when the performance of the WBANs falls below tolerance, utilizing the cell neighbor list established by the beacon method. Simulation results show that the proposed method improves the channel utilization and the network throughput, and in the meantime, reduces the collision probability and energy consumption, when compared with the contention-based beacon schedule scheme.

Framework

The goal of this framework is to provide a low epidemic spread of the disease in an enclosed area. Health data must be ensured to reach the destination in a timely and efficient manner.

Our system consists of the following:

- Cooperative WBAN users in an enclosed area
- Health Portal that authorities of the enclosed area (contact tracers) use to identify close contacts
- Data Store where information collected or generated through the use of BBN network is stored securely

Terminologies Used

- *CooperativeHandshakingamongWBANs* Whenever a WBAN-enabled individual is in range of another user, their coordinators perform a 'digital handshake' by exchanging information. This includes information about health status and wireless signal strength. When a digital handshake occurs between 2 WBAN users, the information that is exchanged is encrypted, so that only the Authorized Data Store can read it. This encryption is like a padlock: anyone can use an open padlock to lock up a box of valuables, but only the trusted person with the key will be able to open it and access what is inside. The probability of the individuals being within 1.5 m of each other is calculated using RSSI (Received Signal Strength Indicator) and Tx Power (Transmission Power). RSSI is used to determine proximity to a close contact.
- *Encounters* An encounter is a series of digital handshakes between two WBAN enabled individuals. Health officials use encounters to determine if a user's period of close contact with any user who tested positive may require further advice on isolation or testing based on the health status.

Epidemic Spread Control Model for BBN Architecture

In this section, we describe all the phases that we have considered to control the spread of epidemic situation. We have considered a 2-tier BBN architecture with cooperating WBANs as shown in Fig. 1. This ensures self-restrained WBANs and quarantine strategies decided by the authorities of the enclosed space of our use case that uses the BBN architecture.

In this system, we have considered a dynamic framework where a person can enter and leave the network at its own pace. Real-time health information is exchanged between cooperative WBANs of the network via their respective coordinators [19]. Using k-means++ algorithms, WBANs form non-overlapping clusters to coordinate efficiently. The authority intercede and provides quarantine strategies based on the exchanged health data preventing infected and infectious people to come in contact with others. We have divided the entire working time into τ continuous aeons. The authorities of the enclosed area keep a count of the *Encounters* during each aeon to accurately determine the period of close contact.

Every epidemic is divided into four stages as shown in Fig. 2. They are as follows:

- *SensitiveStage* This phase is responsive to external conditions or simulations. An individual is vulnerable and thus considered to be exposed to contagious people, but herself not yet infected; may be asymptomatic.
- *InfectedStage* In this phase, an individual is considered a confirmed positive case, but not infectious and communicable.
- *ContagiousStage* In this stage, a person is considered to be infected, infectious and transmissible.
- *QuarantineStage* This stage indicates those individuals who has been identified correctly and removed from the area.

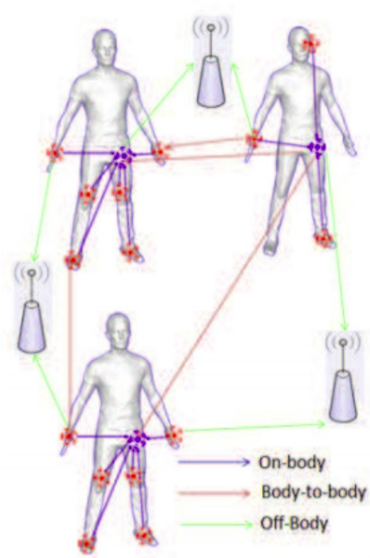


Fig. 1 BBN architecture

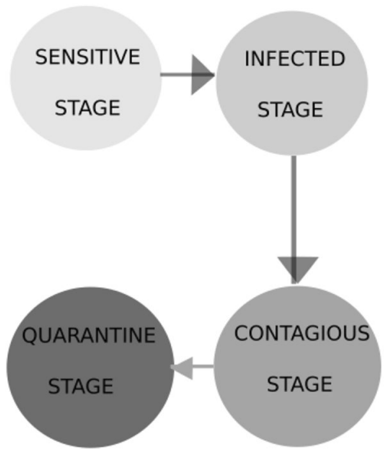


Fig. 2 Stages of epidemic disease

The annotations shown in Fig. 3 are explained in Table 1 at t^{th} epoch.

$S(t)$ represents number of individuals not yet infected, but prone to, at time $t \in \tau$. This is defined as a sensitive stage of the person. $I(t)$ represents those individuals who are infected with the disease, but not yet in a communicable stage. $C(t)$ defines the total number of transmissible individuals. Finally, $Q(t)$ is the number of individuals that have been infected and then removed from the enclosed area. The term 'removed' can be used in different ways like either the person is vaccinated or died or quarantined. In our paper, we have defined it as a person being removed for quarantine for the zone. Every WBAN of a BBN network cooperatively transfers their health status. The flow model provides an idea how the authority intervenes and quarantine an infectious person urgently from the zone based on the exchanged health data. This controls epidemic spread by reducing the contact of infectious people with others.

In our work, we aim to ensure a real-time detection of the epidemic outbreak during the initial phase of the disease where its not yet been contagious.

The mathematical formulation of the stages is given by the following equation:

$$N(t) = S(t) + I(t) + C(t) + Q(t). \tag{1}$$

Table 1 Notations

Symbols	Meanings
$\lambda(t)$	Arrival rate
$\beta(t)$	Close contact/infectious rate of sensitive people with infected people
$\gamma(t)$	Transmission rate
$\delta(t)$	Rate of isolation
μ	Departure rate

In our use case, we have assumed the difference between rate of arrival and departure is negligible. Thus at time t, where $t \in \tau$, there are N number of total individuals in an enclosed area. According to Eq. 1, $S(t)$, $I(t)$, $C(t)$ and $Q(t)$ denote the subset of all individuals present in *SensitiveStage*, *InfectedStage*, *ContagiousStage* and *QuarantineStage*, respectively, at time t.

To guarantee a low epidemic spread, the following epidemic components are used in our system:

$$\beta S(t)C(t), \forall t \in \tau, \tag{2}$$

$$\gamma I(t), \forall t \in \tau, \tag{3}$$

$$\mu(I(t) + C(t)), \forall t \in \tau. \tag{4}$$

Expression 2 is minimized to reduce the contact rate between susceptible and infected persons in the enclosed area.

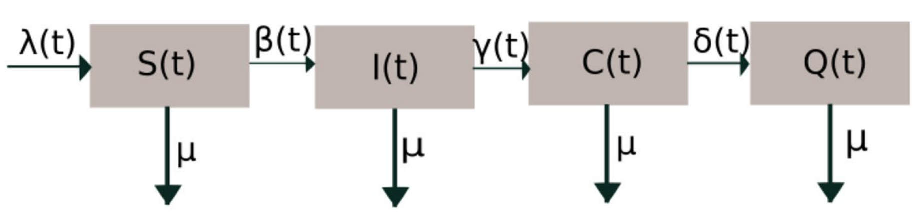
Expression 3 predicts the number of individuals being transmitted from infected to infectious stage using quarantine strategies.

Finally, Expression 4 helps to prevent the dispersion of the disease from the enclosed area to the outside world by tracking and quarantining individuals who area infected or infectious.

Assess Health Status

In our model, each WBAN $n \in N$ should be able to detect his own health status from attached sensors and transmit it to its own coordinator as shown in Fig. 4. The correlated sensor data received for WBAN $n \in N$ is denoted by the following equation:

Fig. 3 Epidemic flow model



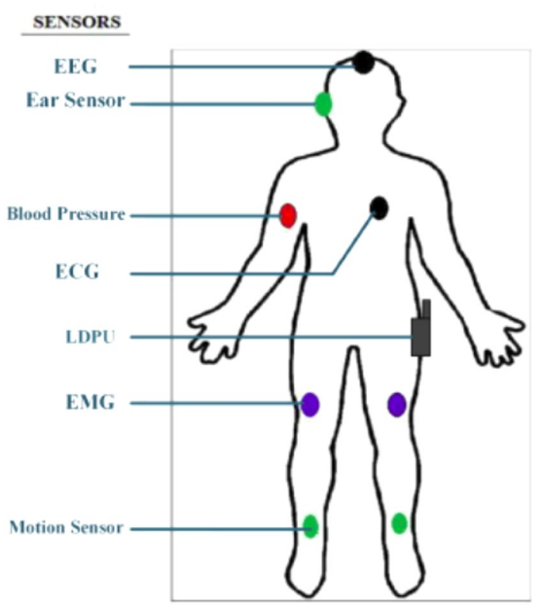


Fig. 4 Intra-WBAN

$$\Gamma_n(t) = \gamma_i(t), \forall i_{\text{sensor}} \in \text{WBAN } n, \tag{5}$$

$$H_n(t) = f(\Gamma_n, t). \tag{6}$$

$f()$ is a deterministic function that uses correlated sensor data received from an individual at time t. It uses statistical methods as defined in [11] to determine health status of the person at time t which is denoted by $H(n)$ as shown in Eq. 6. This technique is an extension of logistic regression for an outcome with three or more ordered categories (in our case, we used three categories of defining health status as given in Eq. 7). The threshold value are depicted in Table 2. This $\Gamma_n(t)$ is transmitted to second tier of the architecture mitigating inter-WBAN interference and is received by the authority level. Now, using Eq. 6, authorities define health status of WBAN $n \in N$, which is denoted by H_n, at time epoch $t \in T$. The values of Table 2 from [6] gives a normal range of different health parameters which we have considered as Threshold value denoted by EP_{th}. The authority matches the received $\Gamma_n(t)$ of WBAN n with Table 2 to determine her H_n. To keep our model simple and practical, the health status is represented by discrete levels as follows:

$$H_n(t) = \begin{cases} 3, & \text{if } f(\Gamma_n, t) \geq \text{EP}_{\text{th}}; \text{Contagious WBAN (C)} \\ 2, & \text{if } \epsilon < f(\Gamma_n, t) \leq \text{EP}_{\text{th}}; \text{Infected WBAN (I)} \\ 1, & \text{otherwise; Exposed WBAN (S)} \end{cases}. \tag{7}$$

Based on Eq. 8, the authority determines the severity of WBAN n. The purpose of Eq. 8 is to trade-off between health data transmission priorities and network resources. This allows WBAN n to broadcast its sensor data to authority:

$$\text{Cost}_n(t) = \alpha E_{\text{res}}(t) + \beta S_n(t) C_n(t) + \gamma I_n(t) + \mu(I_n(t) + C_n(t)) + H_n(t). \tag{8}$$

Inter-WBAN Interference Mitigation

Our model is efficient only if all the data transmissions take place effectively, reliably and timely. Interference significantly affects the quality of communication and can cause incorrect transmission or loss of medical information. Since the attenuation of an electromagnetic wave on the surface of a body is greater than that during general propagation, extensive usage of the network may cause inter-WBAN interferences. Spectrum allocation by clustering is one of the most common methods to mitigate the interferences. For applications that do not require fixed infrastructures (such as base stations), a coloring algorithm can be used. By coloring the division of the cell group, the adjacent cells are of different colors, which reduces or even eliminates the interference of the same frequency. Minimization of types of colors in the algorithm ensures higher spectrum utilization rate. Each color represents a group of channels. The coloring algorithm have the potential to mitigate co-channel interference by enhancing co-channel multiplexing rate under restricted

Table 2 Epidemic threshold for wearables [6]

Clinical evaluation of COVID-19	Measurements	Early warning for COVID-19
Respiratory assessment	RR	≥ 20 bpm
	Lung/heart sound	Crackles
	SpO2	≤ 94%
Cardiovascular evaluation	ECG/HR	Arrhythmia
		HR ≥ 100 bpm
	Cuffless BP	≥ 140/90 mmHg
Clinical symptom monitoring	Body temperature	≥ 38 °C
	Cough	Dry cough

bandwidth of each WBAN. This helps in intelligent partitioning and spectrum allocation for the nodes in the entire region. The coloring algorithm is based on the knowledge of the user location, which can be easily obtained during WBAN application. Although WBANs naturally support cloud computing due to their three-tier architecture, which means that the complex coloring algorithm for all the users in the region can be executed by the server, the frequent topological changes caused by user mobility may consume significant communication and processing resources for simple WBAN devices. In contrast, the inevitable positioning error and different location accuracy for the devices using different positioning methods may also degrade the performance of clustering. For these issues, coloring algorithms is designed that aligns with the capabilities of a WBAN node. Distributed interference-avoidance scheduling of wireless networks can be modeled by the notion of distributed graph coloring, which is commonly adopted in sensor networks or MANET [7, 8, 17]. But, coloring speed is found to be the key factor that affects the performance of inter-WBAN scheduling.

In our system, machine learning is used to improvise the learning process. Reference [5] demonstrated that healthcare offers a different form of data. Different master learning algorithms such as supervised, unsupervised, and enhanced algorithms are used for analyzing this variety of data to increase prediction that can be analyzed using different performance parameters such as exactness, sensitivity, specificity, precision, F1 scoring, and Curve region.

In this paper, coloring process is improvised using an unsupervised learning method to lower the algorithm complexity. As unsupervised learning has the capability of obtaining superior features (such as distance) without prior knowledge, the k-means++ algorithm is designed for WBAN application. This algorithm is used to implement the self-organizing partition of WBAN, and Welsh Powell algorithm ensures minimal number of clusters maximizing effective spectrum allocation. This algorithm ensures a smarter initialization of the centroids and improves the quality of the clustering.

Initially, a random WBAN is selected as cluster center. From this center, shortest distance between other WBANs of the network is calculated. The further a WBAN is from existing cluster center, the higher is its probability to be chosen as the next cluster center. This method ensures that the distance between the newly generated cluster center and the original cluster center is maximized. The flowchart of the algorithm is given in Fig. 5.

The advantages of this procedure to choose cluster center are as follows:

- Based on the density of the area, it can perform adaptive clustering.

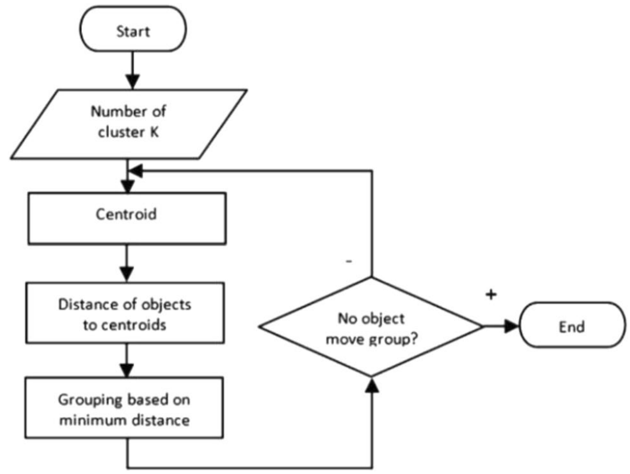


Fig. 5 K-means algorithm

- Effective spectrum allocation is ensured as cell characterization is based on distance.

Although the initialization in K-means++ is computationally more expensive than the standard K-means algorithm, the run-time for convergence to optimum is drastically reduced for K-means++. This is because the centroids that are initially chosen are likely to lie in different clusters already. Moreover, local topological optimization is performed to reduce the computation and processing cost for topological changes. The non-adjacent channels are divided into different groups, and the channel groups used by each cell are determined by vertex coloring. The spectrum is allocated to different cells/clusters dynamically to reduce the interferences for multiple WBANs.

K-means++ algorithm is used to implement the self-organizing partition of WBAN, and the Welsh Powell algorithm is used to allocate the spectrum of each cell.

Performance Evaluation

In this section, first, we have described experimental setup followed by results obtained.

OMNet++-based simulator Castalia−3.2 [2] is used to evaluate routing protocol in BBN network.

Experimental Setup

In this paper, we have considered two use cases as described as follows:

- Case 1: All the cooperative WBANs in an enclosed area are randomly distributed. The distance between two WBANs is not less than 0.5 m. If a WBAN is within a

distance of 1.5 m from another WBAN, it is considered to be in close proximity to each other.
- Case 2: All the cooperative WBANs in an enclosed area are evenly distributed, like a cinema hall, where the distance between two WBANs is 0.8 m.

Data traffic is classified based on Eq. 7. $C(t)$, $I(t)$ and $S(t)$ represent data from Contagious WBAN, Infected WBAN and Exposed WBAN, respectively.

We have considered transmission power of all devices as P_t. Total number of interfering WBANs in a BBN network is considered to be n which are placed at a distance r_k.

Intervention of the system is calculated using Eq. 9 which measures total interference power:

$$I = \sum_{k=1}^{n} P_t r_k^{-4}. \tag{9}$$

To ensure efficient bandwidth utilization, effective clustering is required. This incorporates a better spectrum allocation with minimal signal-to-interference ratio as given by the following equation:

$$\mathrm{SIR} = \frac{P_t r_0^{-6}}{I}, \tag{10}$$

where I is given in Eq. 9. Smaller value of I indicates better interference mitigated system as shown in Fig. 6.

We have assumed a 200 m × 200 m enclosed area. To understand the effect of coloring algorithm used, we have considered a BBN network with three different densities such as 100 WBANs, 70 WBANs and 40 WBANs for each use cases.

In case of our use Case 1, where mobility is high, factually a person remains in his position maximum 3 s. Therefore, probability of keeping original position of WBAN is

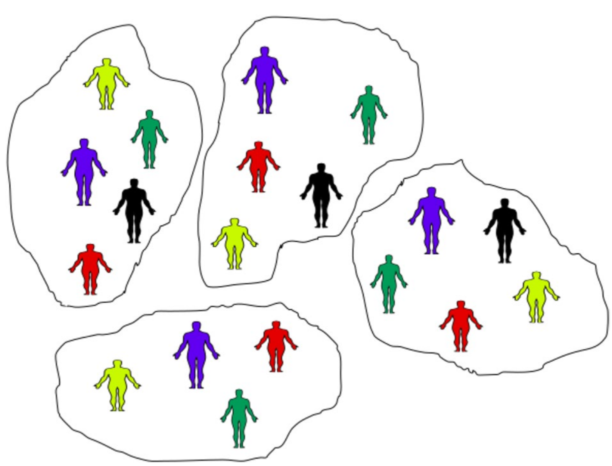


Fig. 6 Intelligent partitioning of WBAN using K-means++ Algorithm

assumed to be 60% for an epoch. Total number of channels is assumed to be 24. We impose this limitation owing to the randomness of the clustering algorithm. Average of 10 experiments is taken to calculate interference value in each cycle. If the difference between two consecutive iterations is less than 10^{-5}, the iteration is stopped.

The authors in [14] proposed a Reliable Routing Technique (RRT) which is a geographic routing protocol, based on GPSR [13]. This works in disaster situation, which signifies partial or complete infrastructure-less condition. This protocol aims in establishing reliable and non-interrupted communication between the rescuers team and affected people. This prioritizes mobile devices of those rescuers that are nearby the location to transfer data. In case the first prioritized device is unable to forward due to weak communication link, the next one in the list forwards the same, ensuring reliability of data delivery in adhoc network. The rescuers were not equipped with sensors. This drawn our attention to use it in a BBN architecture. The routing protocol is evaluated using parameters such as Packet Delivery Ratio (PDR) and Energy Consumption.

Throughput of our system is calculated using Packet Delivery Ratio (PDR) parameter. This is calculated for each type of health data as categorized by different stages of system as shown by the following equation for contagious data:

$$\mathrm{PDR}\ (\%) = \frac{\sum \text{Received C(t) data packets}}{\sum \text{Sent C(t) data packets.}} \tag{11}$$

Table 3 depicts simulation parameters used in our system.

Here, simulation time is taken as 51 s (50 s of data + 1 s of MAC setup) which is divided into 10 epochs.

Results

The results obtained are given as follows.

Figure 7 indicates the number of clusters formed and number of colors required, both increases with increase in

Table 3 Simulation parameters

Parameter	Value
Area	200 m × 200 m
Number of WBANs	[40...100]
Mobility model	Random Waypoint
Transmission power	– 15 dBm
Initial energy	18,720 Joules
Transmission rate	−89.3 dBm
MAC Protocol	BaselineBANMac
Radio model	BANRadio.txt
Propagation model	PathLossMap.txt
Simulation time	51 s

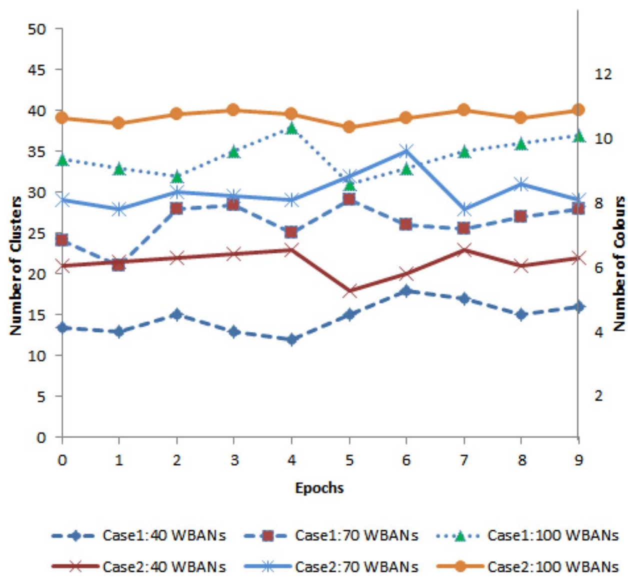


Fig. 7 Average number of clusters vs average number of colors

density in our enclosed 200 m × 200 m area. This is expected because of randomness of clustering algorithm, number of channels in each cell is restricted. Since adjacent channels do not get assigned same colors, thus inter-WBAN interference mitigates. The figure also depicts that used channel group did not change significantly with increase in WBAN density. This justifies appropriate frequency band utilization by unsupervised coloring algorithm for spectrum allocation in multiple WBANs.

Figure 8 shows average interferences due to spectrum allocation used in both the cases. The result concludes that evenly distributed cooperating WBANs outperforms than randomly placed ones in a confined area. Moreover, stability of the coloring algorithm used is justified as interference values do not varies much for both scenarios.

The graph in Fig. 9 illustrates throughput of our system. As given in Eq. 11 throughput is measured in terms of packet delivery ratio for different data types. The result obtained concludes that PDR value deteriorates with increasing WBAN entities in the enclosed area. The result shows that data generated by contagious WBANs are delivered with highest priority as H(t)=2, followed by infectious WBAN data (H(t)=1) and data from Exposed stage WBANs with status H(t)=0. Results obtained are aligned with our health status priorities of Eq. 7. It is worth mentioning that beyond 40 WBANs, PDR of Exposed WBANs data $S(t)$ rapidly deteriorates as resources are occupied by higher priority traffic data. This signifies that precarious WBANs need to be quarantined on a priority basis to efficiently control spread of epidemic. In this density, I(t) and C(t) gets prioritized and thus have better throughput. But as WBAN density gets beyond 70, these two data variants also experience a drop in throughput due to communication overhead packets in the network as shown in Fig. 10. Despite this issue, the priorities are still maintained in delivering data. This ensures that our proposed technique has minimized spread of epidemic disease. Further, our system has been compared with [9, 14]. Reference [9] proposed a novel protocol Cooperative Energy efficient and Priority based Reliable routing protocol with Network coding (CEPRAN) to enhance the reliability and energy efficiency of WBAN using cooperative communication method. The graph clearly indicates that CEPRAN fails to deliver health data efficiently in a mobile scenario. [14] outperforms [9] as it ensures reliable delivery in dynamic scenarios. But, it experience high traffic overhead due to multiple transmissions of data packets. The graph clearly shows that when WBAN density is low, [14] outperforms

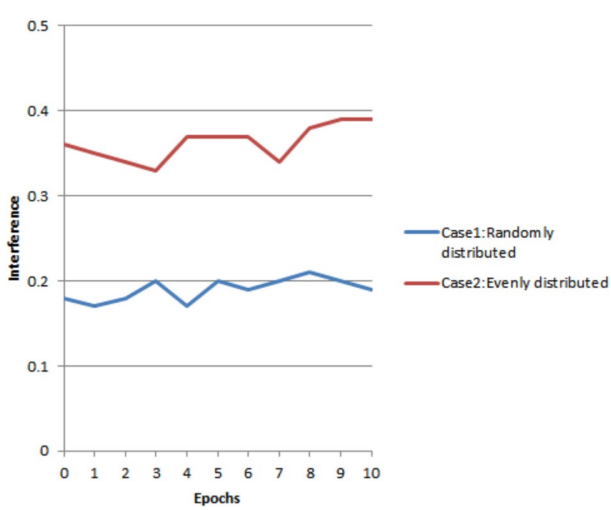


Fig. 8 Interference value of spectrum allocation for different use cases

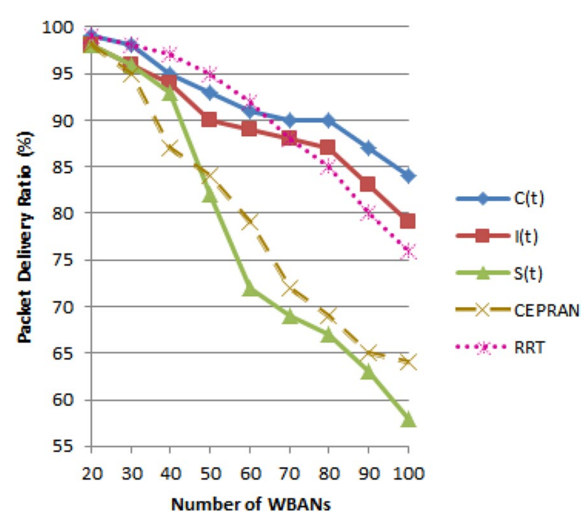


Fig. 9 Throughput of epidemic data

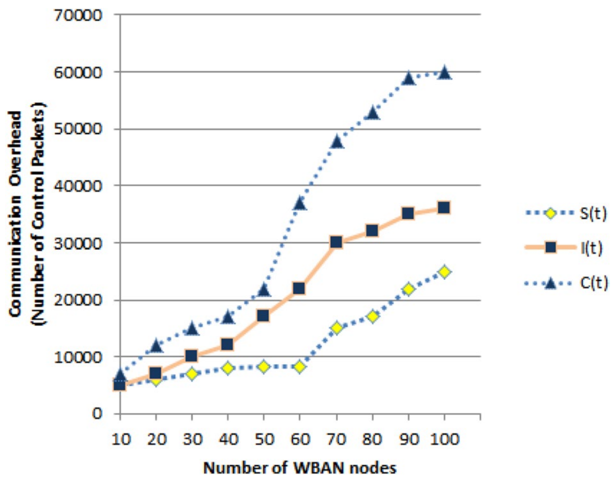


Fig. 10 Communication overhead

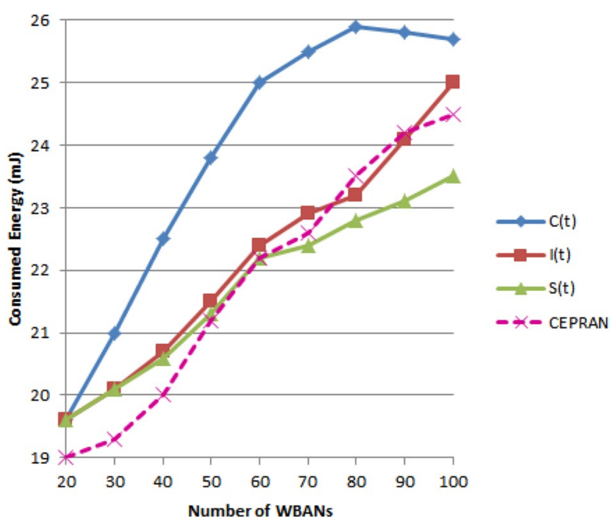


Fig. 11 Energy consumed

others, but with increasing population, prioritized data of our system are better delivered than the rest.

Figure 10 shows the impact of WBAN density on number of control packets in the network. It depicts that the number of control packets of C(t) is maximum as the individual is considered to be critical and all the resources gets allocated on a priority basis for its data to be delivered. The graph also indicates with increasing cooperative WBAN in an enclosed BBN network, communication overhead increases. This goes in agreement with Figs. 9 and 11. As number of WBANs in BBN network increases, communication overhead gets higher resulting in greater consumed energy and a drop in throughput.

Figure 11 shows energy consumption is directly proportional to density of our enclosed area. It is calculated by Resource Manager of the simulator. For each WBAN, it is computed as the total of transmission, buffering, reception and idle energy used. As expected the graph illustrates that WBANs with critical health status $C(t)$ consume maximum energy. This is compared with another cooperative algorithm [9]. Figure 11 depicts that energy consumed in our protocol is more than [9] as they do not take into account interference issue that adversely affect the reliable data delivery.

Conclusion

In this paper, a BBN architecture with cooperating WBANs is considered to control an epidemic spread. We have considered a confined area with two different distribution scenarios. We have also proposed quarantined strategies by minimizing contact between different staged WBANs. An unsupervised learning algorithm is used to efficiently divide the area into non-overlapping clusters. This ensures effective utilization of bandwidth as spectrum is allocated minimizing inter-WBAN interference. Higher throughput and minimal interference guarantees faster propagation of data to the authorities. Based on this health status, the authorities take precise quarantine decisions. Thus, performance analysis of our system guarantee a low epidemic spread of the disease in an enclosed area by enhancing throughput and minimizing interference of our stable system.

Declarations

Conflict of interest On behalf of all the authors, the corresponding author states that there is no conflict of interest.

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