Randomised Collaborative Transmission of Smart Objects

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ABSTRACT
We propose a randomised approach to time and frequency synchronisation of superimposed received signals from collaboratively transmitting smart objects. The technique is feasible without communication between nodes and entirely relies on the receiver feedback. It is practical for an arbitrary number of received signals and transmitter nodes. The superimposed received signal has its maximum constructive interference focused on an arbitrary location of a remote receiver. In both, analytic considerations and in a simulation environment we demonstrate that synchronisation of several hundred received signals is possible within milliseconds.

Author Keywords
Collaborative transmission, Sensor networks, Optimisation, $(1+1)$-EA, Smart Objects

ACM Classification Keywords
C2.7.c Sensor networks, I2.m.c Evolutionary computing and genetic algorithms.

INTRODUCTION
In recent years, computing devices of diminishing size that embed sensing capabilities, communication and actuation have become reality [1, 2, 3]. In [4], nodes of 1-4mm^2 size are discussed so that a paintable or even sprayable network of smart objects may be envisioned that seamlessly integrates into everyday artefacts, cloths or buildings. Consequently, a scenario in which a huge number of communication devices pervasively resides in one or several smart objects is possible. However, at such extreme sizes, energy consumption and lifetime become major concerns for the design of sensing, communication and computing hardware that is integrated in these smart objects. An ambitious solution to power supply at these sizes are parasitically operating nodes that obtain energy, for instance, from solar, environmental movement, temperature change or chemical reactions in living organisms [5, 6]. The energy consumption of parasitic nodes is restricted to several ten microwatts. This greatly impacts the transmission range of parasitic sensor nodes so that information can only be obtained from the network, when the receiver is in direct proximity with the transmitting nodes which is not feasible in many application scenarios [7]. One solution to this problem is to cooperatively transmit information by distinct nodes of a network by utilising constructive interference of the transmitted signals at the receiver. When signal components are simultaneously received, they add up to a sum signal. If they are not synchronised, the interference is destructive, which leads to a distorted signal at the receiver. When, however, identical signal components arrive at a receiver in phase, the interference is constructive and the signal strength is improved. Cooperation can increase the capacity and robustness of a network of transmitters [8, 1] as well as the maximum transmission range [9] and decreases the average energy consumption per node [10, 11].

The use of constructive interference in sensor networks was studied by various groups in the last decade [12, 13, 8, 14, 15, 16, 17]. These approaches utilise neighbouring nodes as relays [18, 19, 20] as originally proposed by Cover and El Gamal in [21]. Neighbouring nodes repeat a recently received signal to achieve a sufficient synchronisation of signals at a receiver. The major drawback of this approach is that the nodes are not synchronised wherefore the location at which a maximum constructive interference of signal components is observed is also a random parameter that depends on several aspects as the placement of nodes, the synchronisation between nodes or the environmental reflection of signal components. For practical applications this means that the receiver has to relocate to find sufficiently synchronised signal components, if there are any.

Cooperative transmission is accomplished in the literature by three distinct approaches: Multi-hop, Data flooding and cluster based.

Multi-hop relaying relies on the physical channel. The multi-hop scenario is interpreted as multi-dimensional relay channel, where communication between all nodes is allowed [22]. It has been shown that this approach optimally divides the network resources in terms of information theoretic metrics [23]. With increasing scenario sizes, this approach is, however, not well suited since the number of transmitted bits per square meter decreases quadratically with the size of the network [24, 25].

An alternative approach that bases on flooding the network with a message that shall be transmitted is presented in [26, 27]. The opportunistic large array (OLA) method utilises the constructive interference of spatially related transmission signals of nodes in a sensor network. Neighbouring transmitters function as relay nodes that retransmit a received signal various times. In this approach the network is flooded with nodes that transmit the desired signal whereby constructive interference is created. A related approach is presented in [16, 15, 28], where the signal is overlaid with white noise to increase the probability of constructive interference. However, for all these strategies the maximum constructive interference occurs at a random point in the transmission range since nodes are not synchronised and also no receiver feedback is utilised.

The third, cluster based approach was first proposed in [29]. The basic idea is to build up clusters of collaboratively transmitting nodes that cooperate when sending or receiving messages [23]. In [30] the optimal cluster design is derived. This approach has the benefit that standard routing algorithms as well as multi-hop theory can be applied with little modification. However, the capacity of a network that follows this topology is lower than for the previously detailed approaches [25, 31].

In contrast to these cooperative approaches we propose to utilise the receiver feedback in order to guide the synchronisation of transmitted signals. By doing this we are able to synchronise a virtually unlimited number of received signals at any concrete target location of a receiver without the need of cooperation between nodes and at a very fast pace. With respect to the fact that no cooperation between nodes is required we refer to this approach as collaborative transmission. In the following sections we demonstrate that it is possible with collaborative transmission to increase the strength of a received signal by a factor that is easily larger than 100 in a fraction of a second.

COLLABORATIVELY TRANSMITTING SMART OBJECTS

We are especially interested in the communication between and with smart objects. The focus of this work is on the sensing, computation and communication components of intercommunicating smart objects. For ease of presentation we refer to such a network of smart objects as a wireless sensor network (WSN), since not the types of smart objects but the number of nodes that contribute in communication is relevant for our approach.

We consider the following scenario. A sensor network of n tiny, square millimetre sized, parasitic sensor nodes is deployed with a high density of sensors per square meter. The information sensed by the sensor nodes is to be transmitted to a stationary remote receiver that is located far off the transmission range of each single sensor node. The receiver can, however transmit a feedback regarding the measured channel quality back to the sensor network. It is possible to measure the channel quality in terms of impulse response of a potentially superimposed channel and to estimate the future channel state by long-term prediction at the transmitter side. This approach is, for example, investigated by the group of Lajos Hanzo at the University of Southampton with focus on the improvement of MISO and MIMO techniques [32, 33, 34]. It requires, however, ambitious capabilities at the transmitter and receiver side and is for that reason currently not feasible for parasitic sensor nodes.

We therefore propose an initialisation phase triggered by the remote receiver. In this phase all nodes simultaneously transmit a predefined signal for synchronisation purposes. The remote receiver compares the received superimposed signal with the expected sequence and transmits the sum difference between both signals as feedback. This feedback guides the synchronisation process at the sensor nodes. When nodes are sufficiently synchronised, the receiver ends the initialisation phase and requests data. Synchronisation between transmitted signals is obtained by phase shifting the baseband signal at the sensor nodes. This can be accomplished for sensor nodes either by utilisation of VCO-elements or by even simpler L/RC-transmitter types. These transmitters enable the easy time/phase shift of a signal by short time alteration of the baseband frequency. In spite of this, these transmitter types are highly error prone so that frequency as well as phase shift are subject to errors. Since the more exact VCO-elements are, however, way more expensive and are not likely to decrease in cost due to manufacturing conditions, we believe that L/RC-transmitters are the only feasible way of implementing parasitic sensor nodes that collaboratively transmit their data.

We investigate the synchronisation process and model the scenario as black-box optimisation problem. The search space of the problem is given by the combined frequency and phase shifted received signals. One point in the search space is given by one configuration of transmitted signals:

$$\sum signal_i(t) \tag{1}$$

W.l.o.g. we assume that a sinus signal at f_{base} =2.4 GHz is transmitted by the nodes so that

$$signal_i(t) = A \cdot \sin(2\pi \cdot (f_{base} + f_i) \cdot t + \varphi_i) \tag{2}$$

with phase shift φ_i and frequency shift f_i defines one configuration of signal i. At time interval t a search point $C(t)$ is given by the set of configurations for all received signals.

$$C(t) = \sum_{i=1}^{n} signal_i(t) \tag{3}$$

The fitness function $f_{fitness} : C \to \mathbb{R}$ is provided by the receiver feedback. W.l.o.g. we assume that the optimisation aim is minimisation. We apply a $(\mu + \lambda)$ evolutionary algorithm to this problem with $\mu = \lambda = 1$, which means that population size as well as offspring population size are 1 and the offspring is chosen as the best (in terms of fitness value) individual of these two. Since population size is 1, no crossover is applied and mutation is the only search operator. The $(1 + 1)$-EA is a natural choice in this problem domain since a population directly refers to one configuration C of the sensor network.

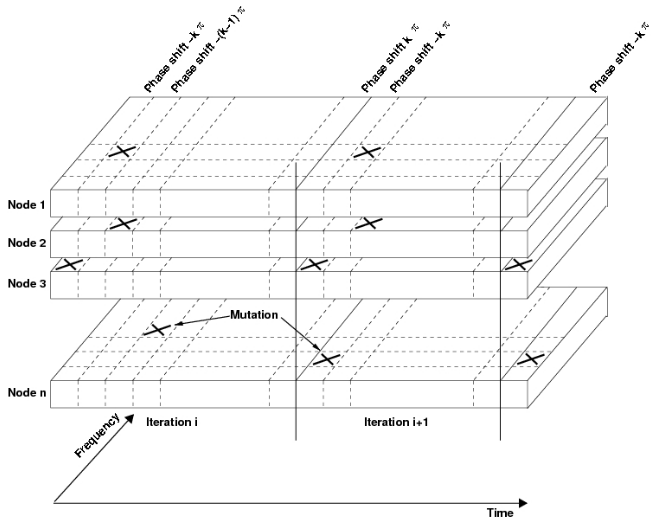

Figure 1. Illustration of the basic scenario. From iteration i to iteration $i+1$ a mutation is applied to sensor node n.

Mutation in the sensor network is obtained without cooperation between sensor nodes. Every node decides randomly after each period of the transmitted signal whether a mutation is applied. In positive case the phase of the signal is altered by a random process. As detailed above, this might also result in frequency alteration. The alteration is maintained in future iterations when the receiver feedback is improved and is reversed otherwise. This principle is illustrated in figure 1. In the figure, node n alters the phase of the transmission signal. Because the fitness value observed in iteration $i+1$ is improved, this alteration is maintained also in iteration $i+2$

In the following sections we present analytic results on the optimisation speed as well as on the performance the approach achieved in simulations.

ANALYTIC CONSIDERATION

In the analytic consideration we aim to estimate the expected optimisation time for a $(1+1)$-EA on the optimisation problem. We assume that the optimisation aim is to obtain perfect synchronisation between all n received signals. This means that all n signals at the receiver have identical phase and frequency.

As discussed above, due to the utilisation of L/RC-elements frequency and phase are potentially distinct between signals. Consequently the periods of the signals are of distinct length as depicted in figure 2. We assume that the actual frequency of the signals is centred around a base frequency while the deviation is guided by a random process. We assume a Gaussian distributed process with a standard deviation of σ. For the analytic consideration, we assume that the fitness value is given by the maximum count of received signals that are in phase:

$$f_{fitness} = \max_i\{|S^i_{\kappa\omega}|\} \tag{4}$$

where $S^i_{\kappa\omega} = \{signal_i(t)|\varphi_i = \kappa, f_i = \omega\}$. We assume that a total of k different phase shifts are possible and consider a maximum of l discrete frequencies.

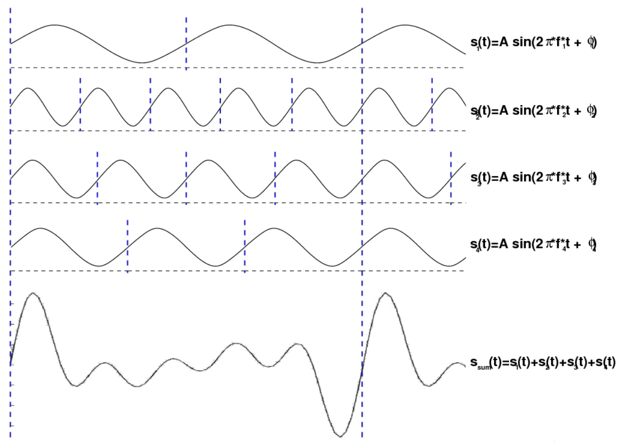

Figure 2. Illustration of periodic relative phase shifts between several signals at various frequencies.

As depicted in figure 2, the relative phase shift between signals of distinct frequencies is not constant over time. However, given any two signals $s_i(t)$ and $s_j(t)$, the same sequence of relative phase shifts occurs repeatedly, and the repentance-frequency is given by the lowest common multiple of the period lengths of the signals. The same mutation of one signal can therefore have different impact on the received sum signal, because the time of mutation also matters. Since, however, the mutation time as well as the mutation itself are guided by random processes, this property does not impact the analytic consideration. We assume a uniformly distributed mutation probability of $p_m = \frac{1}{n}$ for each of the n sensor nodes and uniform distribution of all possible mutation outcomes. Since k distinct phases and l distinct frequencies are considered, a specific mutation occurs with probability $\frac{1}{k \cdot l - 1}$.

In order to estimate the expected optimisation time, we have to understand the optimisation problem a bit better. According to the fitness function, the individuals with worst fitness value have distinct phase and frequency for all $signal_i(t)$ in $C(t)$. Basically, the fitness function is guided by the number of signals that are received synchronously in phase and frequency. The maximum fitness value is therefore given by the number of nodes (n) and it declines every time the largest set of synchronously received signals is increased. We consequently obtain a fitness based partition of the search space with n partitions. The partition with fitness value $f_{fitness}$ is then labelled $L_{n-f_{fitness}}$. The probability to increase the fitness value by at least one is

$$\frac{1}{k \cdot l - 1} \cdot \frac{n - f_{fitness}}{n} \tag{5}$$

since every one of the $n - f_{fitness}$ not synchronised signals is altered in phase and frequency with probability $\frac{1}{n}$ and achieves the specific mutation required with probability $\frac{1}{k \cdot l - 1}$. The optimisation of the $(1+1)$-EA is guided by the fitness function which has the same value for all individuals in L_i but differs for all individuals in L_j with $i \neq j$.

Whenever the fitness value is increased due to a mutation, the current layer L_i is left by the algorithm. In layer i, a total of

$$\begin{pmatrix} n-i \\ 1 \end{pmatrix} = n - i \quad (6)$$

1-bit mutations with probability $\frac{1}{n} \cdot \frac{1}{k \cdot l - 1}$ each suffice to improve the fitness value. We therefore require that at least one of the not synchronised signals is correctly altered in phase or frequency while all other $n-1$ signals remain unchanged. This happens with probability

$$\begin{aligned} & \begin{pmatrix} n-i \\ 1 \end{pmatrix} \cdot \frac{1}{n} \cdot \frac{1}{k \cdot l - 1} \cdot \left(1 - \frac{1}{n}\right)^{n-1} \\ = & \left(\frac{n-i}{n \cdot (k \cdot l - 1)}\right) \cdot \left(1 - \frac{1}{n}\right)^{n-1}. \quad (7) \end{aligned}$$

Since

$$\left(1 - \frac{1}{n}\right)^{n} < \frac{1}{e} < \left(1 - \frac{1}{n}\right)^{n-1} \quad (8)$$

We obtain for the probability s_i that L_i is left and a layer j with $j < i$ is reached due to mutation as

$$s_i \geq \frac{n-i}{n \cdot e \cdot (k \cdot l - 1)}. \quad (9)$$

The expected number of mutations to change the layer is bounded from above by s_i^{-1}. We consequently obtain the overall expected optimisation time as

$$\begin{aligned} E[X] & \leq \sum_{i=0}^{n-1} \frac{e \cdot n(\cdot k \cdot l - 1)}{n-i} \\ & = e \cdot n \cdot (k \cdot l - 1) \cdot \sum_{i=1}^{n} \frac{1}{i} \\ & < e \cdot n \cdot (k \cdot l - 1) \cdot (\ln(n) + 1) \\ & = O\left(n \cdot k \cdot l \cdot \log n\right). \quad (10) \end{aligned}$$

Considering a transmission frequency of 2.4 GHz and $n = l = k = 1000$, this upper bound on the expected time for optimisation corresponds to an expected synchronisation speed of 1.25 seconds.

SIMULATION

We implemented a matlab simulator for collaborative transmission in wireless sensor networks. For the simulations it is assumed that a sine signal of 2.4 GHz is utilised for the initialisation phase of the network. In the simulations a mutation probability of $p_m = \frac{1}{n}$ was assumed for each one sensor node. In a mutation, phase and frequency are randomly altered. We apply a uniformly random phase alteration in the range of $[-\pi, \pi]$ and with stepwidth $0.1 \cdot \pi$. The frequency alteration is guided by a normal distribution with mean μ at 2.4 GHz and standard deviation σ of 10 MHz.

At the receiver the superimposed signals are compared to the expected, perfectly synchronised n received signals. Since both, frequency and phase are subject to alteration, the receiver compares several perfectly synchronised frequency and phase altered signals. In the simulation the received signal is compared to 441 distinct signals which constitute all possible combinations of phase alterations at stepwith $0.1 \cdot \pi$ in $[-\pi, \pi]$ and phase alterations of 1 MHz in $[-10$ MHz, 10 MHz$]$.

The simulation is simplified in that it does not consider multipath propagation and that pathloss for all signal components is considered identical.

Simulation results of a simulation with $n = 1000$ nodes are depicted in figure 3. As it can be observed from the figures, the initial, totally distorted superimposed signal at the receiver is already recognisable after a few hundred iterations. With further iterations the signal is nearly recovered and the main improvements regard signal strength. After 40000 iterations, the amplitude of the superimposed signal is approximately 800 times greater than the amplitude of each one of the received signal components. At a frequency of 2.4GHz, 40000 iterations translate to an optimisation speed of about 17 milliseconds.

OUTLOOK

Despite these impressive results there are still several issues we want to address in future work. The most pressing of these include the consideration of receiver and transmitter movement. While the short synchronisation time should allow reasonable movement at the receiver, a set of moving transmitters might require more advanced synchronisation approaches.

Furthermore, since crossover might speed up the optimisation time significantly, we will consider populations of greater size. To achieve this, several transmit signals per node (distinct phase and frequency shifts) or the division of nodes into various, spatially interweaved, sets that transmit at distinct times are possible approaches to increase the population size.

Additionally, future simulations will also consider path-loss and multipath propagation of signals. Also, a demonstration environment consisting of real sensor nodes is to be implemented and analysed for this scenario.

CONCLUSION

We have demonstrated that communication with smart objects that are equipped with tiny, square millimetre sized communication, sensing and computing components is feasible for ultra-low-power parasitic implementations. Although the transmission range of these smart objects is strictly limited due to power constraints, the transmission range can be greatly improved by collaborative transmission approaches.

We have shown that collaborative transmission in networks of wirelessly interconnected smart devices is feasible without communication between nodes. The problem scenario was modelled as black-box optimisation problem and solved by a $(\mu + \lambda)$ evolutionary algorithm with $\mu = \lambda = 1$. In an analytic consideration we derived an upper bound on the optimisation time of $O(n \cdot l \cdot k \cdot \log(n))$ where n is the size

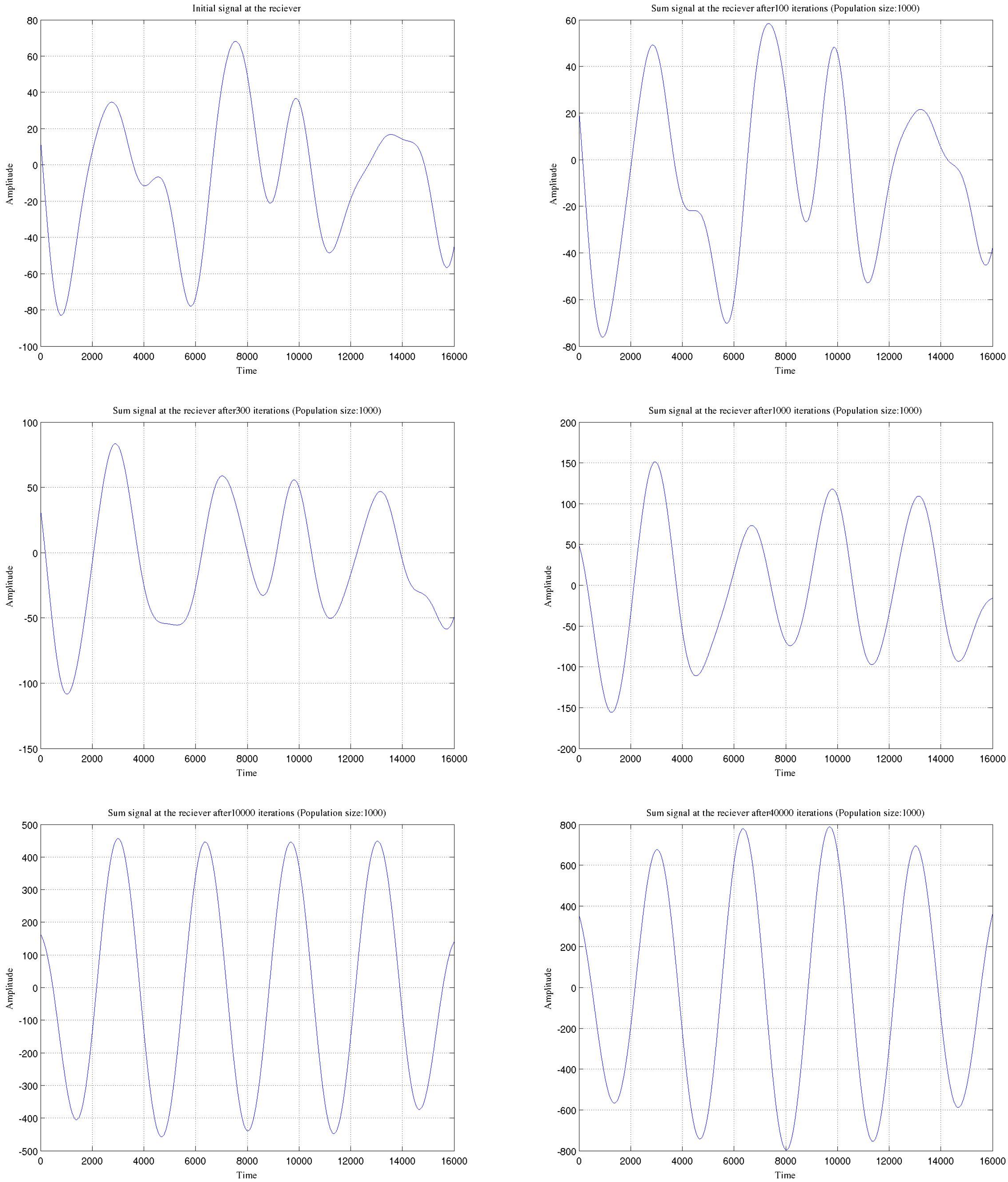

Figure 3. Illustration of the received superimposed signal at various times in the optimisation run.

of the sensor network and l and k describe the amount of variation in phase and frequency.

In a simulation environment we obtained a synchronisation time of about 17 milliseconds and an amplitude boost of the received signal of approximately factor 800 for a network of 1000 collaboratively transmitting nodes at 2.4 GHz.

We conclude that reasonable movement of transmitting or sending nodes is also possible with such rapid initialisation speed.

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