An adaptive protocol for distributed beamforming

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Abstract

We study distributed adaptive beamforming in networks of wireless nodes. In particular, we observe that for the synchronisation of carrier phases, distinct algorithmic configurations are optimal in various environmental settings and propose a protocol that utilises organic computing principles to find optimum parameters. Furthermore, we study the impact of different modulation schemes on the bit error rate of a signal sequence transmitted collaboratively by distributed devices via adaptive beamforming.

1998 ACM Subject Classification I.1.2 Algorithms, I.2.6 Learning

Keywords and phrases Distributed beamforming, Adaptive synchronisation protocol

Digital Object Identifier 10.4230/OASIcs.KiVS.2011.38

1 Introduction

Beamforming is the approach to combine transmission signals from distinct transmit antennas simultaneously in order to create a superimposed signal with improved channel characteristics at a remote location [18]. A necessary condition for beamforming is that the signal streams that are placed onto the transmit antennas are tightly synchronised. One period of a signal transmitted at 2.4 GHz, for instance, lasts only for $0.0004\mu s$. With inaccurate synchronisation among signal streams, the relative phase allocation is therefore likely random. While this very tight synchronisation is achied for centralised beamforming [4], where all antennas are located on one device and the signal streams are controlled by a single controller on this device, it poses a major challenge for distributed beamforming where antennas of distributed devices are utilised for signal transmission [7, 8, 2].

Several open-loop and closed-loop carrier synchronisation approaches have been proposed that enable sufficient synchronisation among carrier signals. These classic approaches are, however, computationally very complex so that an application in wireless sensor networks is not suggestive.

A computationally cheaper but more time consuming randomised interactive closed-loop carrier synchronisation was proposed in [10]. It was analysed for its computational complexity in [9, 15, 16] and several algorithmic improvements have been proposed in [5, 14, 13, 3].

This approach is feasible to be applied in wireless sensor networks due to its low computational complexity for individual nodes. However, despite the numerous studies on this approach, only carrier synchronisation but no actual data transmission was yet studied with this transmission protocol.

17th GI/ITG Conference on Communication in Distributed Systems (KiVS'11).
Editors: Norbert Luttenberger, Hagen Peters; pp. 38–48
OpenAccess Series in Informatics
Schloss Dagstuhl – Leibniz-Zentrum für Informatik, Dagstuhl Publishing, Germany

In our work we present a protocol for this iterative distributed adaptive beamforming scheme and demonstrate the accuracy of data transmission for several modulation schemes in mathematical simulations. Furthermore, we show that the performance of the protocol is impacted by environmental impacts such as the noise figure, movement or activity on the wireless channel but that by adapting several parameters of the transmission protocol, an optimum performance can be achieved for each distinct environment.

We introduce some related work on distributed adaptive beamforming in wireless sensor networks in section 2. In section 3 we show that the synchronisation performance is impacted by environmental settings and introduce a protocol for distributed adaptive transmit beamforming that utilises organic computing principles. In section 4 we study the impact of various modulation schemes on the performance of distributed adaptive transmit beamforming in networks of wireless devices. Finally, in section 5 we draw our conclusion.

2 Distributed beamforming in wireless sensor networks

Algorithms for distributed adaptive beamforming can be distinguished by closed-loop phase synchronisation and open-loop phase synchronisation techniques. Closed-loop carrier synchronisation can be achieved by a master-slave approach as detailed in [17]. The central idea is that nodes transmit a synchronisation sequence simultaneously on code-divisioned channels to a destination node. The destination calculates the relative phase offset of the received signals and broadcasts this information to all transmitters which adapt their carrier signals accordingly.

Due to the high computational complexity burden for the source node to derive the relative phase offset of all received signals and for all nodes due to the utilisation of code division techniques, this implementation is not suggestive in some applications.

Alternatively, a Master-slave-open-loop synchronisation can be applied [6]. In this approach, the relative phase offset among nodes is determined by the transmit nodes with a method similar to [17] but only among transmit nodes. The receiver then broadcasts a carrier signal once so that the transmit nodes are able to correct their frequency offsets. In this method, however, the generally high complexity for the nodes is only shifted from the receiver node to one of the transmit nodes. Therefore, this approach is also hardly feasible in wireless sensor networks.

A simpler and less resource demanding beamforming scheme to synchronise carrier singal components for distributed beamforming is the one-bit feedback based closed-loop approach considered in [17, 8]. The central optimisation procedure of this iterative process consists in n devices $i \in [1, \ldots, n]$ randomly altering the phases γ_i of their carrier signal

$$\Re\left(m(t)e^{j(2\pi(f_c+f_i)t+\gamma_i)}\right) \tag{1}$$

In this signal representation, $m(t)$ denotes the transmit message and f_i the frequency offset of device i to a common carrier frequency f_c. Initially, i.i.d. phase offsets γ_i of carrier signals are assumed. When a transmission from the devices is requested, carrier phases are synchronised in the following iterative process.

1. Each transmitter i randomly alters its carrier phase offset γ_i and frequency offset f_i.
2. Devices transmit as a distributed beamformer.
3. A receiver estimates the amount of synchronisation among carrier phases (for instance by the Signal-to-Noise ratio (SNR) of the received sum signal).
4. This information is broadcast to the transmit devices that interpret it and adapt their carrier phase accordingly.

These four steps are iterated repeatedly until sufficient synchronisation is achieved [9, 11, 12]. Observe that in each of these iterations, a reduction of the SNR is not accepted. A new configuration of phase offsets for transmit carrier components is accepted only when the SNR was increased. Since the search space for the algorithm is weak multimodal [15], this means that the method converges to the optimum with probability 1 [9]. This result achieved in [9] considered an idealised environment without noise and interference. In a realistic environment, the impact of the noise figure determines the accuracy that can be achieved by this approach.

The distinct approaches proposed for this transmission scheme differ in the implementation of the first and the fourth step specified above. In [11, 3] devices alter their carrier phase offset γ_i according to a normal distribution with small variance. In [12] a uniform distribution with a small probability to alter the phase offset of one individual device is utilised instead.

In [9] it was determined that the expected optimisation time of this approach for a network of n transmit nodes is $\mathcal{O}(\log n)$ when in each iteration the optimum probability distribution is chosen. For a fixed uniform distribution over the whole optimisation process, we were able to derive a sharp asymptotic bound of $\Theta(n \cdot k \cdot \log n)$ for the expected optimisation time [15]. Here, k denotes the maximum number of distinct phase offsets a physical transmitter can generate.

When we assume a reasonable number of signal periods for one iteration, this means that, although this synchronisation time is greatly higher than the time required for synchronisation with the classical methods, it is still in the order of milliseconds for reasonable network sizes.

The strength of feedback based closed-loop distributed adaptive beamforming in wireless sensor networks is its simplicity and low processing requirements that make it feasible for the application in networks of tiny sized, low power and computationally restricted devices. However, the impact of environmental settings as well as the bit error rate (BER) achieved by several devices transmitting collaboratively has not yet been considered.

In the following we present a transmission protocol that utilises this synchronisation scheme and that is in addition responsive to environmental impacts.

3 Adaptive distributed beamforming protocol

In one-bit feedback based distributed adaptive transmit beamforming, devices combine their carrier signals to collaboratively reach a remote receiver. In recent studies we have already observed some hints that the phase synchronisation performance might be dependent on environmental parameters. These parameters are, for instance, the probability to alter phases of transmit carriers, the noise figure, the distance between transmit devices and a remote receiver or the count of devices participating in the synchronisation [14, 13, 16]. Figure 1 exemplary shows the impact of the network size on the synchronisation process. We observe that the best phase alteration probability to achieve an optimum BER for collaborative transmission differs among various network sizes. Consequently, optimum parameters have to be derived individually for each concrete scenario.

Therefore, we propose a protocol for distributed adaptive beamforming that incorporates self-adaptation and self-optimisation features. The protocol adapts the parameters of the iterative synchronisation to a given environment so that an optimum synchronisation performance is achieved.

All devices utilise the iterative distributed carrier synchronisation detailed in [10, 6]. In order to adapt to different environments, devices maintain and adapt the following parameters.

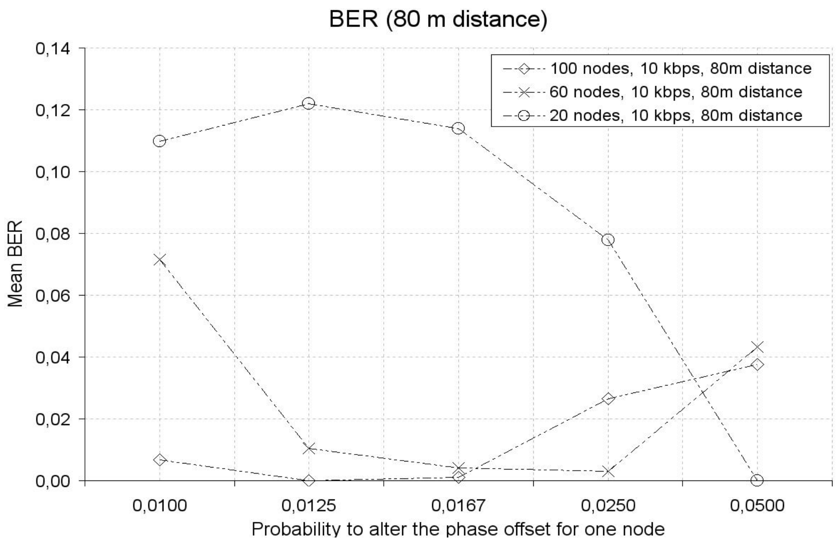


Figure 1 Impact of the network size on the BER at distinct phase alteration probabilities for one bit feedback based distributed phase synchronisation and adaptive transmit beamforming

$\boldsymbol{P_{mut,i}}$ Probability to alter the phase offset of an individual device i ($P_{mut,i} \in [0,1]$)
$\boldsymbol{P_{dist,i}}$ Probability distribution for the random process of device i ($P_{dist,i} \in \{\text{normal, uniform}\}$)
$\boldsymbol{var_i}$ Variance for the random process ($var_i \in [0,\pi]$)

The transmission protocol consists of the following steps that are executed in order.

1. An individual device broadcasts a data sequence s_d to devices in its proximity.
2. Devices decide whether to participate in the transmission. Possible decision parameters are, for instance, the energy level, a required count of participating devices or current computational load.
3. Closed-loop one bit feedback based carrier synchronisation is achieved (cf. section 2). Devices utilise $P_{mut,i}$, $P_{dist,i}$, var_i.
4. Upon sufficient synchronisation the receiver broadcasts an acknowledgement.
5. Optimisation parameters $P_{mut,i}$, $P_{dist,i}$ and var_i are adapted.
6. Devices collaboratively transmit s_d.

For a given environment, a set of devices can with this protocol improve their synchronisation performance after several transmissions.

The protocol is self-adaptive to a given environment and self-healing as it automatically adapts the optimisation parameters to changing numbers of participating devices or communication topologies.

We evaluate this protocol in mathematical simulations in a network of 100 devices. The scenario of distributed adaptive beamforming in an environment of distributed devices was implemented in Matlab. In the simulation, we calculate the phase offset of the dominant signal component from each transmit device at the remote receiver based on the transmission distance between the nodes in a direct line of sight (LOS) scenario. Path loss was calculated by the Friis free space formula ($P_{tx}\left(\frac{\lambda}{2\pi d}\right)^2 G_{tx}G_{rx}$) with antenna gain for the transmitter and the receiver as $G_{rx} = G_{tx} = 0dB$. Signals are transmitted at $2.4GHz$ with transmit power $P_{tx} = 1mW$.

Table 1 Configuration of the simulations. P_{rx} is the the received signal power, d is the distance between transmitter and receiver and λ is the wavelength of the signal

Property	Value
Node distribution area	$30m \times 30m$
Location of the receiver	$(15m, 15m, 30m)$
Mobility	stationary devices
Base band frequency	$f_{base} = 2.4$ GHz
Transmission power of devices	$P_{tx} = 1mW$
Gain of the transmit antenna	$G_{tx} = 0$ dB
Gain of the receive antenna	$G_{rx} = 0$ dB
Iterations per simulations	6000
Identical simulation runs	10
Random noise power [1]	-103 dBm
Pathloss calculation (P_{rx})	$P_{tx}\left(\frac{\lambda}{2\pi d}\right)^2 G_{tx}G_{rx}$

All received signal components calculated in this manner are then summed up in order to achieve the superimposed sum signal

$$\zeta_{\text{sum}}(t) = \sum_i \left(\Re\left(m(t)e^{j(2\pi(f_c+f_i)t+\gamma_i)}\right)\right) \tag{2}$$

Finally, a noise signal $\zeta_{\text{noise}}(t)$ is added on to $\zeta_{\text{sum}}(t)$ to calculate the signal at the receiver. We utilise ambient white Gaussian noise (AWGN) with $-103dBm$ as proposed in [1].

Short of multipath propagation the simulation therefore captures all relevant aspects of the radio channel in our scenario. In particular, the channel is not modelled by a statistical distribution but calculated on a LOS basis.

Devices are distributed uniformly at random on a $30m \times 30m$ square area with a receiver located up to $200m$ above the centre of this area. All devices are stationary and frequency and phase stability are considered perfect (cf. Table 1).

Each simulation lasts for 6000 iterations and one iteration consists of the devices transmitting, feedback computation, feedback transmission and feedback interpretation. It is possible to perform these steps within few singal periods so that the time consumed for a synchronisation of 6000 iterations is in the order of milliseconds for a base band signal frequency of 2.4 GHz.

Signal quality of a signal during the synchronisation phase is measured by the Root of the Mean Square Error (RMSE) of the received signal ζ_{sum} to an expected optimum signal ζ_{opt}:

$$RMSE = \sqrt{\sum_{t=0}^{\tau} \frac{\left(\zeta_{\text{sum}}(t) + \zeta_{\text{noise}}(t) - \zeta_{\text{opt}}(t)\right)^2}{n}} \tag{3}$$

In equation (3), τ is chosen to cover several signal periods.

The optimum signal is calculated as a perfectly aligned and properly phase shifted received sum signal from all transmit sources. For the optimum signal, noise is disregarded.

We utilise an optimisation approach that implements a uniform distribution to alter the phase offset of distributed carrier signals. Consequently, only the mutation probability $P_{mut,i}$ of devices $i \in [1..n]$ is altered. After each 10 successful synchronisations, the mean achieved RMSE is compared to recently achieved RMSE values and the phase alteration probability is adapted accordingly. As all nodes receive identical feedback from the receiver device, this adaptation process is identical among devices.

We implement the search for the optimum mutation probability as a divide and conquer approach. Nodes start with a mutation probability of 0.5 and then subsequently approximate

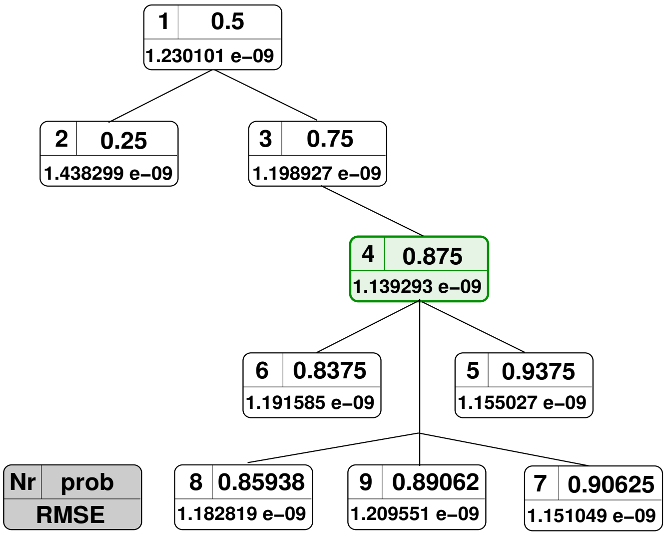


Figure 2 Schematic of the optimisation process of the proposed protocol. RMSE values depicted denote the mean RMSE after 10 synchronisations with identical $P_{mut,i}$

the optimum mutation probability by testing those parts of the search space with lower and higher probability. The process always follows the phase alteration probability with the best achieved RMSE after 10 synchronisations. Figure 2 schematically illustrates this optimisation process in a network of 100 devices that are located approximately 30 meters from a remote receiver.

All devices first complete synchronisations with $P_{mut,i} = 0.5$ and then derive the mean RMSE values for $P_{mut,i} = 0.25$ and $P_{mut,i} = 0.75$. Since the latter probability achieves a better RMSE in this simulation, the lower half of the probability space ($P_{mut,i} \in [0, 0.5]$) is disregarded in the synchronisation process. With 0.875 a probability is reached for which no further improvement is found. In order to derive an optimum value, the algorithm tests additional three probability values in the proximity of the best value reached so far and then exits with the optimum derived mutation probability of $P_{mut,i} = 0.875$ in this case.

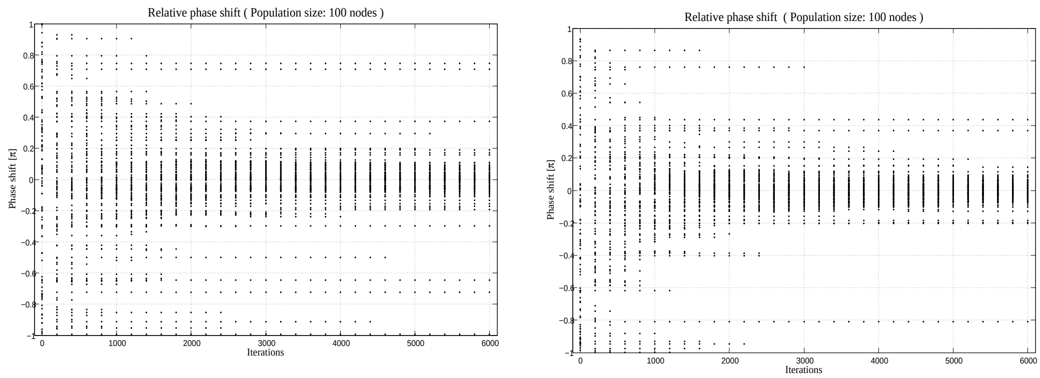
Figure 3 depicts the relative phase offset of all carrier signal components during the course of the synchronisation for $P_{mut,i} = 0.5$ and $P_{mut,i} = 0.875$. We observe that the synchronisation in the latter case is better since the variance in the phase offsets achieved for all nodes is lower.

We can see this also from the sequence of RMSE values observed by the remote receiver as depicted in figure 4. The synchronisation with $P_{mut,i} = 0.875$ is faster and achieves an improved RMSE during the synchronisation.

In general, the algorithm searches the probability space in a binary search fashion in order to bound the optimum mutation probability. Figure 5 depicts the RMSE values achieved in this process in an environment where the receiver is located 50 meters apart from the transmit devices.

4 Modulation and data transmission

When carrier signal components are sufficiently synchronised, transmit devices simultaneously start transmitting their message $m(t)$. The distinct signal components are then superimposed at the remote receiver. Naturally, as synchronisation is not perfect, we expect a considerable



(a) Distributed carrier phase synchronisation with $P_{mut,i} = 0.5$

(b) Distributed carrier phase synchronisation with $P_{mut,i} = 0.875$

Figure 3 Relative phase offset achieved during distributed carrier phase synchronisation processes

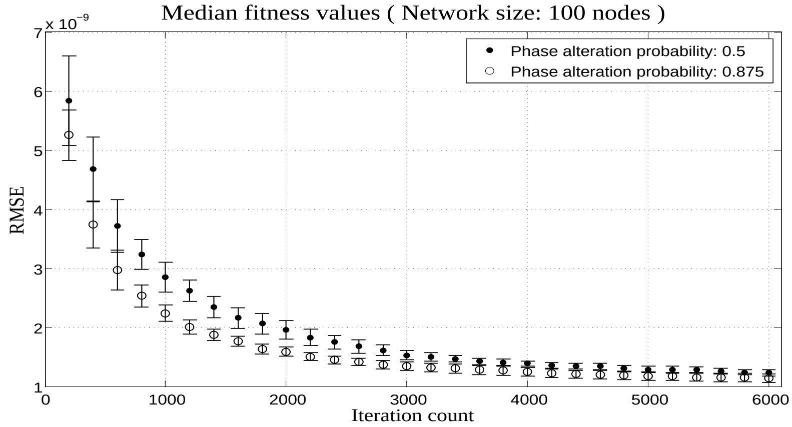


Figure 4 Median RMSE values achieved in the course of the synchronisation

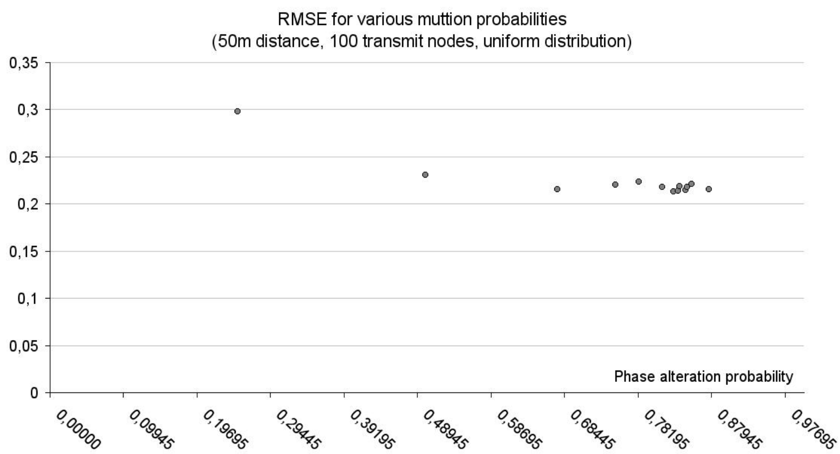


Figure 5 Mean RMSE values after each 10 synchronisations for various phase alteration probabilities $P_{mut,i}$

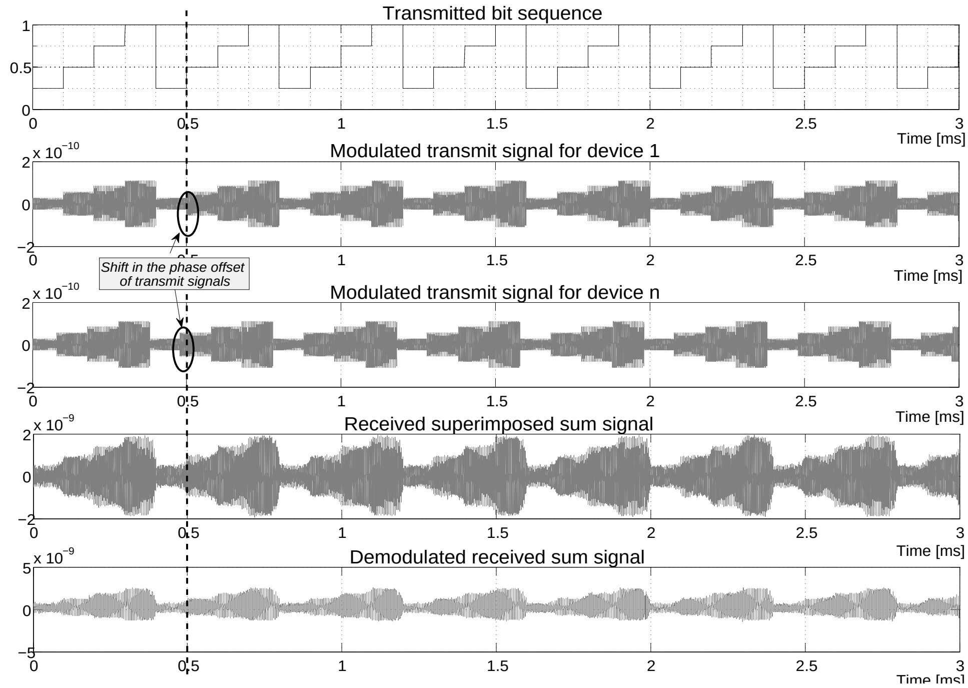


Figure 6 Modulation and demodulation of a simple symbol sequence

bit error rate for this transmission. We study the bit error rate achieved by distributed beamforming devices for various transmission distances and modulation schemes. We again utilise the simulation environment introduced in section 3.

After each complete synchronisation (6000 iterations) all 100 devices transmit an identical signal sequence $m(t)$. We utilise a simple amplitude modulation scheme. At the receiver the BER of the received and demodulated signal is calculated.

After synchronisation is achieved, a message signal $m(t)$ is modulated on the transmit carrier and simultaneously transmitted by all devices. Figure 6 illustrates the process of modulation, transmission and demodulation.

In this modulation scheme, two bits are modulated for one transmitted symbol. We modulated a simple periodical symbol sequence on the transmit carrier of each single node. In the figure, we observe a considerable carrier phase offset of the two nodes depicted. For this environmental setting we observe that the received superimposed signal is improved in its signal strength compared to a single transmit signal. Also, the symbol sequence is clearly visible from the received superimposed signal. Consequently, the bit error rate (BER) for this configuration is low. Figure 7 depicts the BER for three amplitude modulation schemes and for various transmission distances.

In all simulations, 100 transmit devices are utilised to superimpose their carrier signals. In the other two modulation schemes, three and one bits are represented by one transmit symbol, respectively. As expected, we observe that the BER is higher with the higher modulation scheme and with increasing distance. While it is neglectable for the weaker modulation scheme at a distance of 30 meters, the BER becomes significant with increasing distance for all modulation schemes.

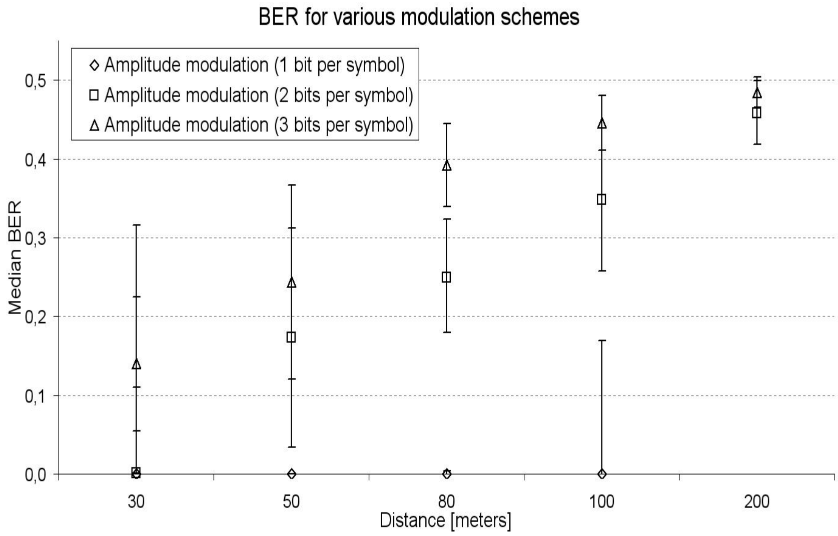


Figure 7 Bit error rate for three amplitude modulation schemes

5 Conclusion

We have introduced an adaptive divide and conquer protocol for data transmission among distributed adaptive beamforming devices that adapts to environmental settings in order to achieve optimum synchronisation between beamforming devices. The protocol builds on a recently proposed computationally cheap randomised iterative beamforming algorithm. We extend the current work by demonstrating the bit error rate for actual data transmission with several modulation schemes.

In mathematical simulations of networks of 100 beamforming devices we have demonstrated that the synchronisation quality is actually improved by the proposed protocol in the long term. The parameters of the synchronisation protocol are then adapted to environmental conditions to achieve the best accuracy under these conditions.

Additionally, we studied various amplitude modulation schemes for beamforming transmissions. We could observe that a collaborative data transmission is possible also at distances of about 200 meters when strong bit guarding schemes are utilised. At shorter distances of about 30 meters the BER observed was neglectable for lower order modulation schemes.

Our studies confirm the feasibility of randomised iterative feedback based carrier synchronisation for beamforming of distributed computation and transmission power restricted devices.

Acknowledgements The authors would like to acknowledge partial funding by the German Academic Exchange Service (DAAD) through the FIT postdoc grant in the project ‘Implicit situation awareness of a wireless sensor network utilising channel quality estimations‘.

We would further like to acknowledge partial funding by the ’Deutsche Forschungsgemeinschaft’ (DFG) for the project ”Emergent radio” as part of the priority program 1183 ”Organic Computing”.

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