Self-Optimized Collaborative Data Communication in Wireless Sensor Networks

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ABSTRACT

Collaborative data communication is one of the efficient approaches in wireless sensor networks (WSN) in terms of life-time, reliability and quality of service (QoS) enhancement. In this paper, we propose a new self-optimized collaborative algorithm which minimizes the energy consumption by decreasing the number of collaborative nodes and at the same time guarantees the demanded quality. To do this, we focus on the fact that during the collaboration, a receiver node aggregates the signals of the collaborative nodes separately. The major task of this node is the time adjustment of the collaborative nodes to receive their signals synchronously. The proposed algorithm performs an extra process to sort the aggregated signals based on their bit error rate (BER) as the quality and select the minimum number of the nodes with higher rank for collaboration. It is because the low quality signals have negative effect on the collaboration performance, as confirmed experimentally. The new algorithm gains higher level of energy storage balance without increasing of the inter-node communications or computational load by modification of the node selection metric. It also guarantees the demanded QoS through modification of the collaboration based on the signal quality at the destination which results in higher reliability. Based on the proposed algorithm, sensor nodes can gain the optimum efficiency during collaborative data communication without external management resources. The algorithm is applicable in various scenarios and network structures.

Categories and Subject Descriptors

C.2.1 [**Computer Communication Networks**]: Network Architecture and Design—*distributed networks, wireless communications*

General Terms

Algorithms, Design, Performance, Measurement

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Keywords

Collaborative data communications, Self-optimization, Quality of Service, Life-time, Reliability

1. INTRODUCTION

In spite of the limitations in the sensing, processing, communicating and energy storage capabilities of the sensor nodes, WSNs are developing in our everyday life to enhance the quality by extending the smart living environments (smart-home or office), ubiquitously sensing of the human health features (pervasive healthcare), etc. Although the advances in electronic designs mitigate the constraints of WSNs, the dependency of the current WSNs to external management resources restricts their applications. One natural solution to this problem would be to extend the self-organization and optimization capabilities [8] within the WSNs. It enables the sensor nodes to organize themselves automatically and without external help and modify their operations adaptively in order to maintain optimum efficiency, reliability and life-time.

The limited energy resources of the sensor nodes and also higher energy demand for data communication rather than other functions (sensing or processing), has turned the data communication in WSNs into a challenging issue. On the one hand, sensor nodes need to actively communicate with each other to improve the QoS but on the other hand, to extend their life-time, they have to minimize the energy consumption. In some scenarios like body area networks, smart home and most of the WSNs developed for residential or industrial environments, sensor nodes use constant energy resources or are recharged manually. But energy efficiency is still one of the important issues considering the need to save as much energy as possible when feeding a large group of nodes or to postpone the next required charging phase. The same criteria hold for sensor nodes equipped with energy harvesting modules. Due to the scarcity of available energy, increased energy efficiency would mean increased node activity. Moreover, time-dependent situation of the nodes and WSNs makes real time optimization inevitable. Therefore, self-optimization of the WSNs in terms of energy efficiency has attracted great attention, *e.g.* in [6] the operation of the sensor nodes (sensing and data communication) in tracking of a moving target is optimized by modeling the WSN as an ant colony, or in [5] [7] inspired by biological approaches, routing algorithms are optimized automatically.

One of the efficient data communication techniques to minimize energy consumption is collaborative data communication [3] [9] [1]. Due to the decreasing of the overall interference level by directional communication and distribution of the energy consumption among the collaborative nodes (which avoids early death of some of the sensor nodes), collaborative data communication considerably increases the network life-time. In this technique, instead of individual data communication, groups of sensor nodes at the transmitter or receiver side collaborate in a transmit [3] [9] or receive [1] collaboration process.

Despite the vast researches about collaborative data communication, there are still some open questions. For instance, to the best of the authors' knowledge, there is no idea how to estimate the optimum number of collaborating sensor nodes. While the overestimation of this parameter decreases the energy efficiency, its underestimation results in an inefficient collaboration and decreases the quality of the communicated signal. Besides, different parameters such as noise, interference, channel fading, battery storage, or mobility of the nodes result in different capabilities of the sensor nodes to contribute in collaboration. However, most of the previous works (e.g. [1], [3] and [9]) are based on the selection of a group of neighboring nodes for collaboration.

Obviously estimation of the optimum number of collaborative nodes as well as the selection of the most capable nodes improves the collaboration performance. Due to the variations in the network and sensor nodes' status, this optimization scenario should be handled during the network operation and based on the current state. The necessity of decreasing WSNs' need to external management resources is another reason to extend self-optimization approaches.

There are some researches to develop self-X features in routing algorithms [5] [7] or in communicating protocols [6], but to the best of our knowledge, the idea of self-optimized collaborative data communication is not yet being investigated. Therefore, in this paper, our focus is on the self-optimized collaborative data communication. After a review of different current collaboration methods and a discussion over the effective parameters on the collaboration performance, challenges and opportunities offered by self-optimization of the collaborative data communication will be investigated. Afterwards, the proposed ideas are applied to one of the current collaboration algorithms which yields an efficient self-optimized collaborative data communication algorithm. Experimental results and computer simulations are presented to support the theoretical discussions. The examinations confirm the improved life-time and reliability of data communication in WSNs.

2. COLLABORATIVE COMMUNICATION

Collaborative data communication can be realized either in transmission or reception sides. collaborative sensor nodes set a virtual array and adjust their time delays to increase the directivity of the virtual array during signal transmission/reception. The following subsections are devoted to the detailed explanation of collaborative data communication.

2.1 Transmit Collaboration

Transmit collaboration is mostly known as transmit beamforming. Similar to other beamforming systems, provided that the transmitter is equipped with multiple antennas and the time delays of the signal of each antenna is set properly, the multiple signals combine constructively at the destination node, *i.e.* the proper phase shifts generate a directive pattern toward the receiver. Directional data transmission has positive effect on the overall network interference level [10]. Considering the fact that signal quality at the receiver depends on the signal to noise and interference ratio (SINR), it is possible to maintain a fixed quality while reducing the transmission power. The phase adjustment and array elements' number and position play a key role in the beamforming efficiency [10]. In WSNs, factors such as the random distribution of the sensor nodes, ambiguity about the sensor nodes' relation, poor connection of the sensor nodes (wireless communications with unknown time delays), separate RF subsystems and limited energy and processing resources, make the realization of classical transmit beamforming impractical.

Mudumbai *et.al.* have proposed a transmit beamforming algorithm for WSN applications [3]. Depending on the network policy, data is usually transmitted following a predetermined schedule or after reception of a request from the destination node. Collaboration is clicked by the setting up of the virtual array and sharing of the transmitting signal by the source node (the node which has some data to transmit). The procedure is followed by synchronization and adjustment of the time delays of the collaborative nodes. Following proper time delay assignment, the transmitted signals are combined constructively at the destination node (the receiver node). To accomplish this, various methods with different accuracy, energy consumption and time delays have been proposed [9] [4]. One of the rather simple synchronization methods that is full-feedback closed-loop method [11] presented in figure 1. As seen in figure 1-a, the destination node sends a synchronization message through the virtual array. Collaborative nodes receive the signal and after detecting the message, send it back through the destination node via their own sub-channel (figure 1-b). Assuming the same processing time for all of the collaborative nodes (due to the variety of the sensor node's tasks and sharing of the processing resources, the time between the reception and transmission of this message differ for various nodes), proper time shifts are estimated at the destination node from the feedbacks. The destination node sends the timing data back to the collaborative nodes (figure 1-c). At this stage, the collaborative nodes are ready for data communication. They send the signal simultaneously with lower power than that of individual data communication and also the destination node receives the constructive combination of the transmitted signals (figure 1-d). Obviously, the transmission power in the other directions decreases with respect to the array beam-pattern.

Transmit collaboration keeps the sensor nodes' energy storage balanced by the distribution of the energy consumption among the collaborative nodes. It also decreases the interfering signals from the other nodes due to the directive data communications. Transmit collaboration increases the transmission range. This feature is useful to decrease the time delay during multi-hop communications. Therefore, in comparison with individual communication, transmit beamforming decreases the overall network power consumption. Figure 2 represents the corresponding beam-pattern to a random distributed set of five collaborating sensor nodes.

The above mentioned advantages are at the expense of some extra local communications during initialization and interaction between the collaborative nodes and the destination nodes. Therefore, depending on the number of collaborative nodes, the length of the communicated message

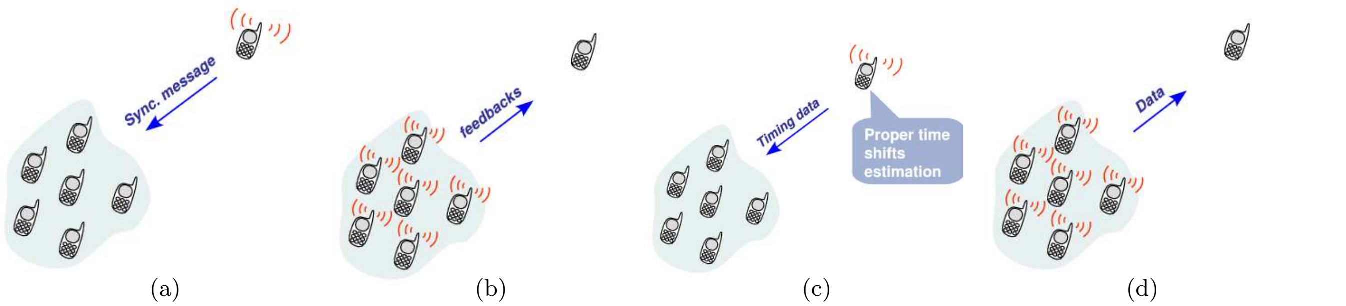


Figure 1: Different steps of transmit collaboration; a. Transmission of the sync. message, b. Processing of the sync. message and sending it back, c. Proper time shifts estimation and sending to the collaborative nodes, d. Application of the time shifts and simultaneously data transmission by the collaborative nodes

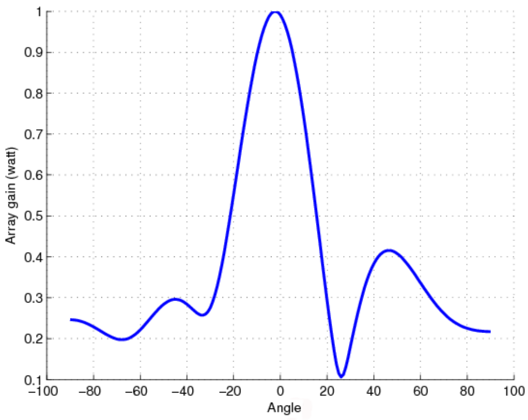


Figure 2: Illustration of a sample beam-pattern generated by collaborative sensor nodes

and the distance between the collaborating and destination nodes, the amount of collaboration energy efficiency varies. It means that the efficiency can be optimized by adjusting the effective parameters.

To formulate the dependency of energy efficiency to the effective parameters, it is assumed that the collaborative nodes are determined and the collaboration process is initiated. According to [1] and [2], the associated energy consumption to the sharing of the communicated signal, synchronization and data communication steps are respectively, $T_d \cdot P_S$, $(2M+1) \cdot T_m \cdot P_{Lc}$ and $M \cdot T_d \cdot P_{Lc}$. Therefore, the overall energy consumption during collaboration would be $E_c = T_d \cdot P_S + (2M+1) \cdot T_m \cdot P_{Lc} + M \cdot T_d \cdot P_{Lc}$, where T_d and T_m are the lengths of the data stream and communicated messages to initiate collaboration, and P_S and P_{Lc} are transmission power of inter-nodes and long-range communication. To guarantee the demanded quality, the transmission power should be more than $L + SNR_{min} + N$, where N is the additive noise power, SNR_{min} is acceptable SNR and L is the transmission loss which according to the Friis equation, depends on the distance (l) and frequency (f) as $L = 20logl(km) + 20logf(MHz) + 32.45$. Similarly, energy consumption during individual data communication is $E_i = T_d \cdot P_{Li}$, where P_{Li} is the transmission power for long range individual data communications. Due to the different channel effects in the individual and collaboration cases, different transmission powers are considered. Defining energy efficiency as $e = (E_i - E_c)/E_i$, we have

$$e = \frac{T_d \cdot P_{Li} - (T_d \cdot P_S + (2M+1) \cdot T_m \cdot P_{Lc} + M \cdot T_d \cdot P_{Lc})}{T_d \cdot P_{Li}} \tag{1}$$

As observed, energy efficiency is affected by the length of the communicated messages for initialization of the collaboration or data communication and the transmission power during inter-node or long rage communications. The transmission powers are affected by the environmental noise and interference and the distance between the nodes (L). Energy efficiency is further discussed in the next sub-section.

Due to multi-path effect, the received signal consists of several components which have been through different paths and this makes the time delay estimation process difficult. Therefore, the key role of the time delays in transmit collaboration restricts its application to line of sight (LOS) scenarios. Even if the time delay is estimated properly, because of reflection from different paths, the signal quality and power in non-LOS cases suffer severe degradation. Miniaturization and mobility of the sensor nodes, which especially in pervasive computing and wearable applications are desired, intensifies this problem. Decreasing the updating intervals to have more suitable signals at the receiver is also impractical due to high energy consumption.

2.2 Receive Collaboration

Inspired by transmit collaboration, in receive collaboration [1] and [2], after setting up of the virtual array and synchronization (similar to transmit collaboration), all of the collaborative nodes receive the transmitted signal by the remote node. Afterward, one of the collaborative nodes is selected as the coordinator node to aggregate the signals and apply proper array processing algorithm. The received signals are synchronous at the collaborative nodes. But the random distribution of the collaborative nodes and hence different inter-node distances disturb the synchronicity. Without performing an extra synchronization step among the collaborative nodes, aggregated signals at the coordinator node would not necessarily be synchronous. In this case, application of receive collaboration is restricted to very low bit-rate communications so that in comparison with the bit duration, the differences among the inter-node time delays

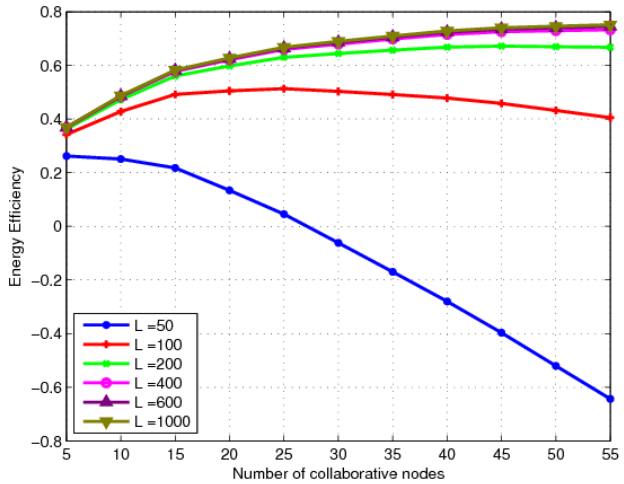


Figure 3: Impact of L: the distance between collaborative and destination nodes and M: the number of collaborative nodes on the energy efficiency

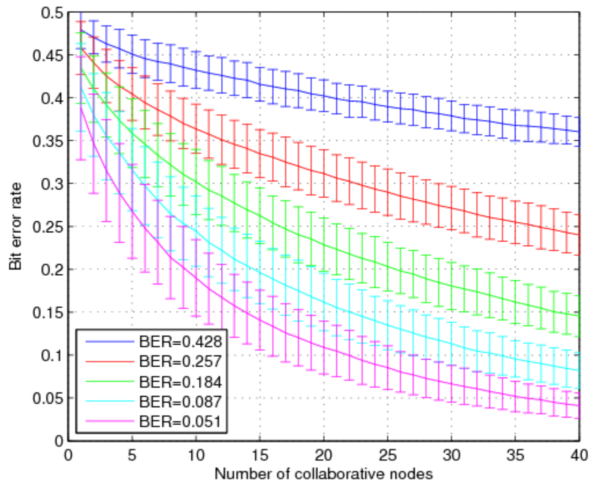


Figure 4: Impact of the selection of the best M nodes on the collaboration energy efficiency: 40 nodes participate in the collaboration and only M of them are selected

are negligible. Proper modifications in the synchronization step to remove these limitations are discussed in [2].

According to the duality theorem, transmission channel and antenna pattern (both for single and array antenna) have the same behavior in transmission and reception modes. Therefore, assuming fixed collaborating and destination nodes, the corresponding time delays of transmit beamforming are also applicable in receive mode. During the combination step, the coordinator node is responsible for the combination of the receiving signals. Similar to the transmit collaboration, non-LOS communication and multi-path have negative effects on receive beamforming. Similar calculations for receive collaboration are in [2] and the results of the analytical analyses are visualized in figure 3. In this figure, assuming fixed data stream length and constant distance between collaborating and destination nodes (L), the energy efficiency for various numbers of collaborative nodes (M) is calculated. This analysis is repeated for different values of L. As observed, increasing of M has different effects on the energy efficiency. Depending on L, it causes some increase in the energy efficiency. The curves are saturated and tend to be decreasing, *e.g.* when $L = 100m$, efficiency saturated after rather high increment from $M = 5$ to 15. With the collaboration of more than 15 nodes, deterioration in the energy efficiency is observed. Moreover as L increases, to gain optimum energy efficiency, more collaborative nodes are required.

3. SELF-OPTIMIZATION

In the previous section, it was shown that current collaboration approaches are not at their optimum level in terms of energy efficiency and reliability. In this section, we propose a self-optimized collaborative data communication algorithm.

3.1 Self-Optimization Ideas

Before introduction of the self-optimized algorithm, the optimization ideas are presented in this sub-section.

3.1.1 Optimum Nodes' Count

In the previous section, based on the analytical analysis, we showed that proper number of collaborative nodes (M) can optimize the energy efficiency during collaboration. And the optimum M depends on the distance between the collaborating and destination nodes (L) and length of the communicating data (T_d). Although these analyses represent the impact of the effective parameters on the energy efficiency, some simplifications especially in transmission channel model, decrease the accuracy. Furthermore, the application of this optimization technique is restricted to the scenarios in which the distance between collaborating and destination node, is known in advance. Also, considering the time variant status of the sensor nodes and the network, real-time optimization of the collaboration requires extra processing and communications to update the effective parameters in the energy efficiency.

Since there are several time-variant parameters affecting the minimum number of collaborative nodes to minimize the energy consumption and at the same time guarantee the demanded QoS, the superposition of the collaborative nodes' signals at the destination node should be somehow qualified to find the minimum M. On the other hand, to keep the energy efficiency high, the proposed method should not load extra communication or computation. To realize this, we lay our focus on the synchronization step in which, the destination node receives the feedbacks from each of the collaborative nodes via independent sub-channels (*e.g.* in distinct time slots in TDMA based networks). Assuming the same quality and therefore no priority for the sensor nodes to participate in the collaboration, after synchronization of the signals and estimation of the proper time delays, the destination node estimates the optimum number of the collaborative nodes by sensing of the aggregated signal quality (BER) for different values of M. Variation of this parameter is represented in figure 4 for different levels of individual

Table 1: The measured BERs according to the experimental analyses

Cases	BER_1	BER_2	BER_3	$BER_{(2,3)}$	$BER_{(1,2,3)}$
A	0.3296	$4.8e$-4	0.0102	$2e$-5	2.6e-4
B	0.3913	0.0043	0.0164	$6e$-5	0.0018
C	0.399	0.0086	0.024	$3.2e$-4	0.0055

signal quality (average BER). As seen, BER is saturated in all of the curves but for the high quality ones it happens at lower BERs. It means that to minimize the collaborative nodes count, the individual signal qualities should also be considered. For instance, in case of desirable BER = 0.2, using quality level 3 (BER = 0.184), 25 sensor nodes should participate in the collaboration. Increasing the overall signal quality by using the curves corresponding to BER = 0.087 and 0.051 decreases the minimum number of collaborative nodes to 15 and 9 respectively which is mainly due to the increased probability of the existence of proper signals at the superimposed output.

If the collaborative nodes do not satisfy the desired quality, the destination node sends a command to reset the collaboration starting with higher number of collaborative nodes. During collaboration, due to the variation of the transmission channel or sensor nodes situations, the optimum value of M may change. Proper feedbacks from the destination node revealing the signal quality can re-optimize this parameter.

3.1.2 *Selection of the Higher Quality Nodes*

Although in the last sub-section, an optimum number of collaborative nodes was extracted due to non-realistic assumption of the same quality for the entire participating sensor nodes, collaboration is still not optimum in terms of energy efficiency. There are some reasons listed below which negatively affect the quality of the collaborative nodes signal in the destination node.

- Due to the small dimensions of the sensor nodes in comparison with the objects surrounding them in most of the applications, even small objects may block the line of sight (LOS) connection with the remote node. The transmission loss of non-LOS channels is relatively high because of the reflection from surfaces.
- As mentioned before, non-LOS links degrade also the beamforming performance by affecting the time delay estimation process.
- Based on their location and strength, interference and noise resources also contaminate the signal in WSNs.
- Physical damages to the sensor nodes' antenna, time variant operation of the sensor nodes or battery depletion are also other known reasons responsible for the signal quality degradation in WSNs.

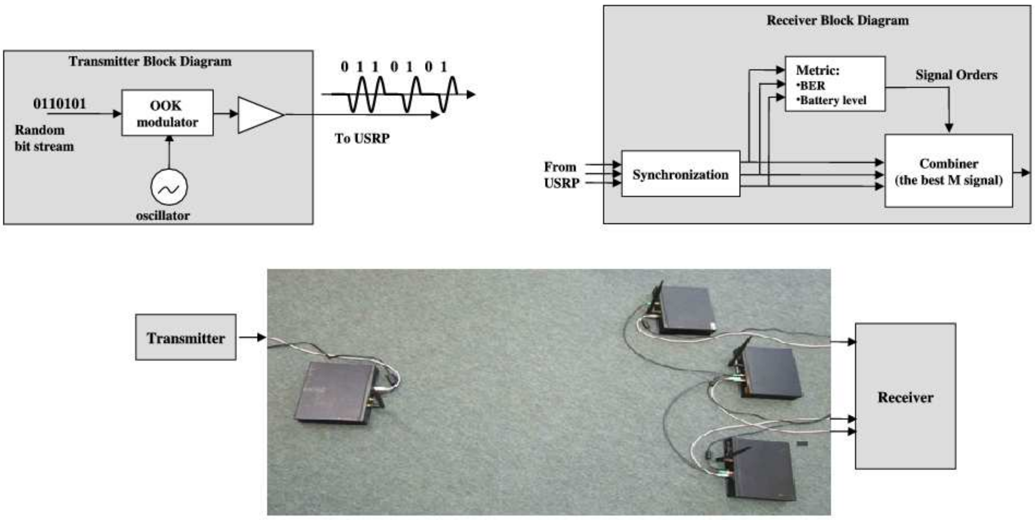
Negative impacts of the low quality superimposed signals are investigated experimentally in figure 5. To ease the implementation, the scenario is based on receive collaboration but the results are also valid for transmit collaboration. In this test, we used USRP[1] software radio as the communication sub-system of the sensor nodes. The processing of the sensor nodes are performed at the computers connected to the USRPs via USB connections. Figure 5-a presents the experimental setup and the schematic of the required sub-systems at transmitter and receiver sides. In this scenario, there is one transmitter in the left (N_0) and three independent receivers in the right (N_1 to N_3). At the transmitter side, an OOK (*on-off-keying*) signal is generated at 900 *MHz* carrying a random digital bit stream. This signal is then transmitted via free space channel and is received by the receiver USRPs which are attached to another computer. Since all of the received signals are saved at the same computer, collaborative nodes do not need to select a node to manage the collaboration and send their signals to. Finally the participating nodes are sorted in term of their signal quality. The combiner module senses the BER of the superimposition of the first M signals to find the minimum number of the collaborative nodes to guarantee the demanded signal quality. In this case, M varies from 1 to 3. Communication of a bit stream enables us to test the previously suggested ideas accurately by measuring BER.

To show the impact of the individual signal quality on the collaboration performance, we change the quality of one of the receiver nodes (N_1) by bending its antenna which would decrease the reception gain. Afterwards the impact of the improper sensor nodes on the collaboration is evaluated in three cases with different signal quality (BER). For each case, samples of the captured signals are presented in figure 5-b to 5-d. The corresponding calculated BER of each signal is summarized in Table 1. In all cases, the signal received by N_1 (sketched at left) is of lower quality compared to the other nodes. According to Table 1, the quality of the receiving signals by N_2 and N_3 are relatively good in case A whereas in case B with increasing BER the quality deteriorates and finally in case C the worst quality is observed. Comparison of the BERs at the last two columns of Table 1 shows that not only N_1 has no positive effect on the collaboration, it also decreases the quality of the superimposed signals. Comparison of the BERs in cases A - C shows that the negative effect of low quality nodes on the collaboration increases by a decline in the overall signal quality. It means, to have positive effects on the collaboration, the participating sensor nodes should have qualities higher than a threshold, otherwise their impacts would be destructive. This threshold is calculated based on the average BER of the participating nodes and the demanded BER.

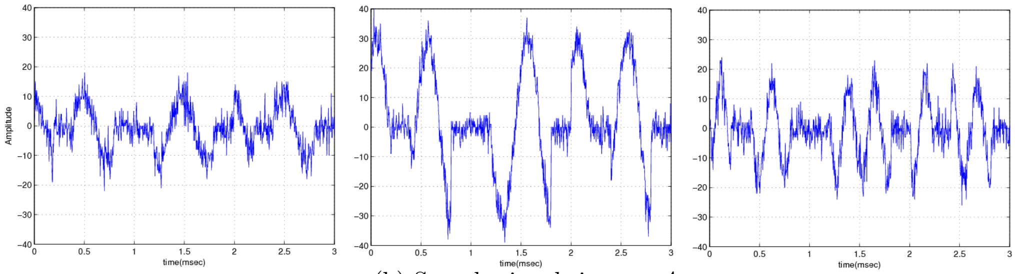
On the other hand, following the previous discussion, the quality of the sensor nodes' signal is time dependent and so their capabilities to participate in the collaboration vary by time. Therefore, optimum sensor nodes should be selected automatically and without external helps.

In most of the synchronization methods, destination node receives the signals of the collaborative nodes separately via one of the multiple access methods. Each received signal contains information about the quality of the channel (noise and interference level and transmission loss) between its corresponding node and the destination node. Since the collaborative nodes use the same transmission power, comparison of the received signals quality is a suitable and practical metric to sort the sensor nodes and pick the first M out of them. To guarantee the quality of the collaboration output, the node selection process can be performed based on the comparison of the signal quality with a fixed or adaptive threshold which is estimated based on the overall received

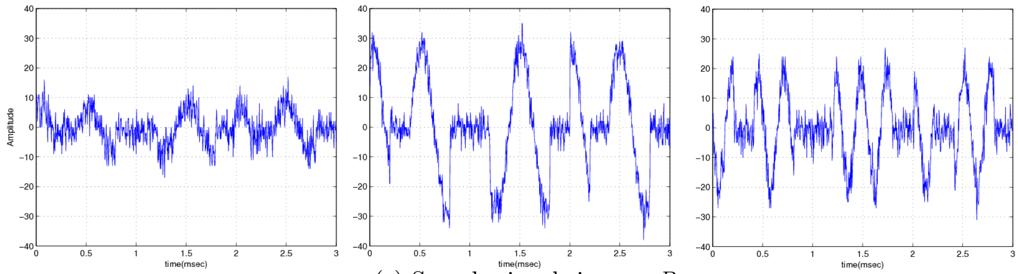
[1] www.ettus.com



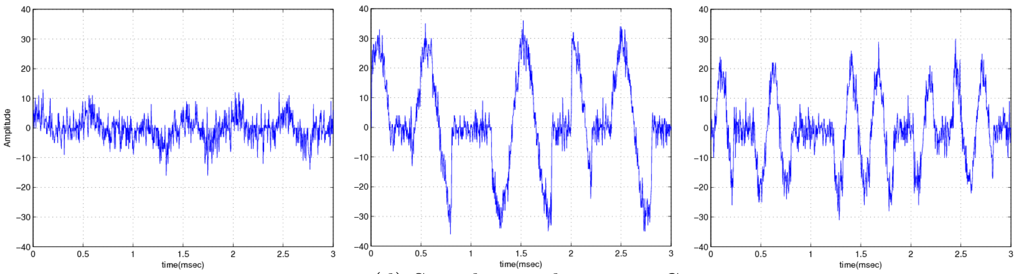
(a) Experimental scenario, relation of the USRP nodes and transmitter and receiver block diagrams



(b) Sample signals in case A



(c) Sample signals in case B



(d) Sample signals in case C

Figure 5: Experimental setup and sample signals at different test cases

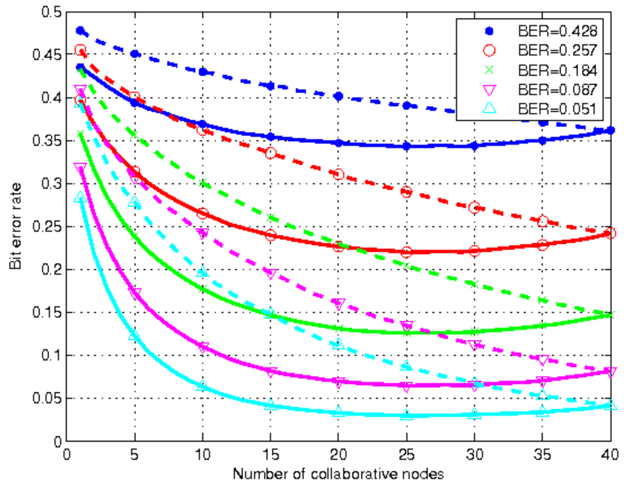


Figure 6: Comparison of the minimum number of collaborative nodes to gain different values of BER for the proposed and conventional methods

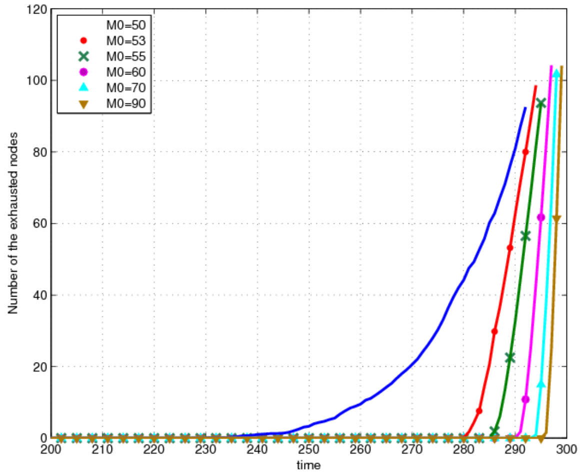


Figure 7: Illustration of the positive Impact of the proposed algorithm on the Life time

signals quality. Obviously, in the case of having less than M qualified signals, this step is repeated with a larger number of collaborative nodes.

There are other synchronization methods (*e.g.* [7]) in which the collaborative nodes do not transmit their signal separately to the remote node. However still in such methods the rejection of the improper nodes can be fulfilled via some modifications in the previously proposed technique. For example. in receive collaboration, depending on the collaboration mode, the destination node sends signals to the collaborative nodes. Before these signals are received by the collaborative nodes, they undergo different transmission channels. The coordinator node aggregates samples of the received signals to evaluate their quality, sort them and select proper sensor nodes. Finally it announces the accepted nodes for the collaboration. For these kinds of collaboration methods, our optimization idea increases the inter-node communications.

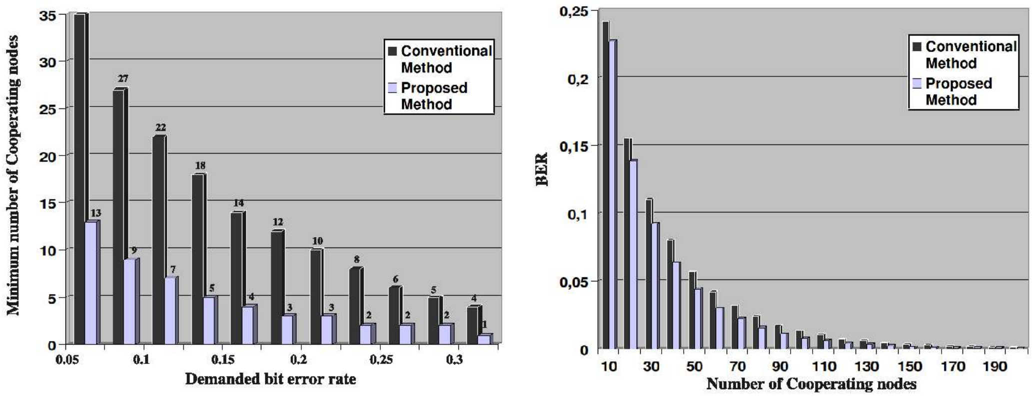
The effectiveness of the suggested approach is shown in figure 6. In this figure, there are two sorts of BER curves; the dashed curves representing the BER of the superimposed signals based on the conventional collaboration and the solid curves, the BER of the superimposed signals according to the suggested method. In comparison with the conventional method, the curves representing the BER of the proposed method decrease faster by increasing M. In other words, in the proposed technique to gain a certain value of the BER, less collaborative nodes and so less energy consumption is needed. Since sorting of the nodes is based on their corresponding signal quality, the first signals have the highest quality. Therefore, in comparison with the case of random selection (conventional method), their superimposition yields lower BER. But by increasing M, new signals have lower quality. Therefore, after some values of M, their effects are positive but low and at the last part of the curves the impact of the additive nodes are destructive due to increasing of the BER. Figure 6 confirms also the achievements at the experimental investigations (figure 5 and table 1).

3.1.3 Balancing of the Battery Storage

If located in the hot spots or in the vicinity of strong noise or interference or when sent through extremely lossy transmission channel, some of the sensor, might have to increase their activity or transmission power which would lead to early energy exhaustion. The early death of some of these nodes degrades the WSNs performance by leaving holes in the coverage area. To balance the energy resources of the sensor nodes by the distribution of the power consumption among the collaborative nodes is considered as one of the collaboration advantages.

A higher level of energy balance is still possible by considering the energy storage level in the optimum node selection metric. When the signals are sorted based on signal quality and energy storage level, due to having higher rank, the more qualified nodes with higher battery storage are selected for collaboration. To realize this idea, the energy level data can be attached to the feedback signals which are sent to the destination node.

Figure 7 represents the improvement in balancing battery exhaustion by considering the energy storage level as a complementary metric in the node selection process. In this figure, it is assumed that in a WSN composed of 150 sensor nodes, data transmission is performed collaboratively with 50 nodes. For the ease of simulation, the same message length and also the same transmission power is considered. Therefore, each data communication costs a fixed amount for energy of the collaborative nodes. The examination ends when only 50 active nodes remain. In the conventional method, there is no priority in the participating nodes whereas in the new method, at first M_0 nodes participate in the node selection stage. Assuming the same signal quality, the destination node picks the participating nodes with the highest energy level up. Different participating node counts are examined in figure 7. As expected, even a few extra nodes ($M_0 = 53$ or 55) has significant positive



(a) Approach I

(b) Approach II

Figure 8: Impact of the suggested algorithm on the minimum number of collaborative nodes: Comparison

effects on the energy storage balance and network life-time. The effectiveness rate of the number of participating nodes decreases by increasing M_0. Although the energy consumption during this stage is relatively low, to keep the energy efficiency high, M_0 should be selected properly, based on the demanded balance level and acceptable communication load.

Although this modification in the selection metric increases the collaboration efficiency to balance the energy storage level, it adds an extra processing and communicating load to the collaboration initialization phase which limits the energy efficiency.

In case of the same priority for energy storage level and channel quality (transmission loss, noise or interference), to simplify the selection metric even more, merging of the two suggested metrics is applicable. To do so, instead of sending some extra signals representing the energy levels, sensor nodes relate their transmission power to their energy storage level. Since, low quality signals are assumed to be either lossy transmission channel or high noise and interference level or low battery storage, they can be rejected from collaboration by sorting the signals only according to their quality. This idea is used in the next subsection to propose a simple self-optimized collaborative communication method.

3.2 Self-Optimization Collaborative Algorithm

In the previous sub-section, several suggestions were made to optimize the collaborative data communication performance. In this section, the mentioned collaborative communication algorithm is modified based of these suggestions and the new procedures are presented in Table 2. Although applied to transmit collaboration, it can be generalized to receive collaboration as well. The new underlined modifications are made in the synchronization and node selection steps. The most computational load is that of the destination node to sort and pick up the proper nodes. In the implementation of the proposed algorithm two different approaches can be considered:

Approach I: Participation of a fixed number of sensor nodes in the collaboration and selection of the minimum number of them to obtain a certain BER.

Approach II: Participation of M_0 sensor nodes and selection of $M = ceil(\alpha \cdot M_0)$ nodes with the highest quality where $0 < \alpha < 1$, where $ceil(x)$ is the higher integer number before x.

The impact of both approaches on the number of collaborative nodes is demonstrated in figure 8. The grey bars represent the number of collaborative nodes needed to obtain different values of BER (horizontal axis) in the first approach whereas the black bars correspond to the conventional method. Similar to that of figure 6, $M_0 = 40$ sensor nodes are assumed to participate in the collaboration. They are synchronized by the destination node and the minimum number of nodes which satisfy the desired BER (which varies from 0.05 to 0.3) is selected. In the conventional algorithm, the BER of the superimposed signals is calculated for different number of collaborative nodes and although non-realistically, it is assumed that the minimum number of sensor nodes collaborate together. In practice, due to lack of feedbacks from the signal quality, even more nodes should be involved in the collaboration process to ensure reliability.

In the second scenario (figure 8-b), different number of sensor nodes participate in the collaboration 80 percent of which with higher qualities are selected. As observed, either approaches yield to a decrease in the number of collaborative nodes whereas with the first one, higher efficiency can be achieved. This is mainly because of the availability of more candidates at the destination node to be selected for collaboration which increases the chance of having more high quality signals. Moreover, the efficiency further decreases with an increase in BER. On the other hand, as depicted in figure 8-b, since the proposed algorithm (with the second approach) removes the low quality nodes from the collaboration procedure, better signal quality with lower number of collaborative nodes is achieved. This result is further confirmed during the experimental analysis in figure 5.

Although the number of collaborative nodes gives a rough estimation of the operation of the proposed algorithm, more precise performance comparison in terms of energy consumption is presented. To do so, following the steps of Table 2, the consumed energy by the two approaches to reach different BERs are compared in figure 9-a and 9-b. During the simulations, at each BER, referring to figure 8 minimum number of collaborative nodes to guarantee the sig-

Table 2: **Psudo-code of the proposed algorithm, D: Destination and C: Collaborative nodes**

Description	at
Initialization	C
Broadcast a request for participation	D
Share the transmitting signal	C
Accept the collaboration by sending an acknowledgment message	C
Synchronization and node selection	D
Transmit a sync. message to the collaborative nodes	D
Estimate proper transmission power based on the battery storage	C
Receive the sync. message and sending it back	C
Estimate proper time shifts for collaborative nodes	D
Sort collaborative nodes based on their signal quality (BER or SINR)	D
Aggregate the first M superimposed signals to find minimum M to gain demanded quality	D
If (proper M is achieved)	
Send the timing and membership (accepted/rejected) data to the collaborative nodes	D
else	
send a command to reset the collaboration with higher number of nodes	D
Data transmission	C
Adjust the time shifts	C
Transmit the shared signal simultaneously	C
Receive the constructively Combination of the superimposed signals	D

nal quality is achieved via both approaches as well as via conventional algorithm. All communicated messages during synchronization and node selection steps have the same length (T_m). The test is then repeated for different lengths of communicating data (T_d).

As seen in figure 9-a, the energy consumption of the conventional algorithm has uniform behavior at logarithmic scale (approximately one decade decrease versus BER from 0.05 to 0.3) whereas the first approach of the proposed algorithm has different behavior for different values of T_d. To discuss more about the results, we define the following two terms of energy consumption:

- Energy consumption during initialization step (synchronization and node selection), E_{init}, which depends only on M_0 and T_m.
- Energy consumption during data communication (E_{com}) which depends on T_d and the number of collaborative nodes (M_0 in the conventional algorithm and M in the proposed algorithm).

Energy consumptions referring to the proposed and conventional algorithms are shown with index of P and C. Therefore, the total energy consumption in these two algorithms are

$$E_C = E_{initC} + E_{comC} \tag{2}$$

$$E_P = E_{initP} + E_{comP} \tag{3}$$

According to the previous discussions, we have

$$E_{initC} < E_{initP} \tag{4}$$

$$E_{comC} > E_{comP} \tag{5}$$

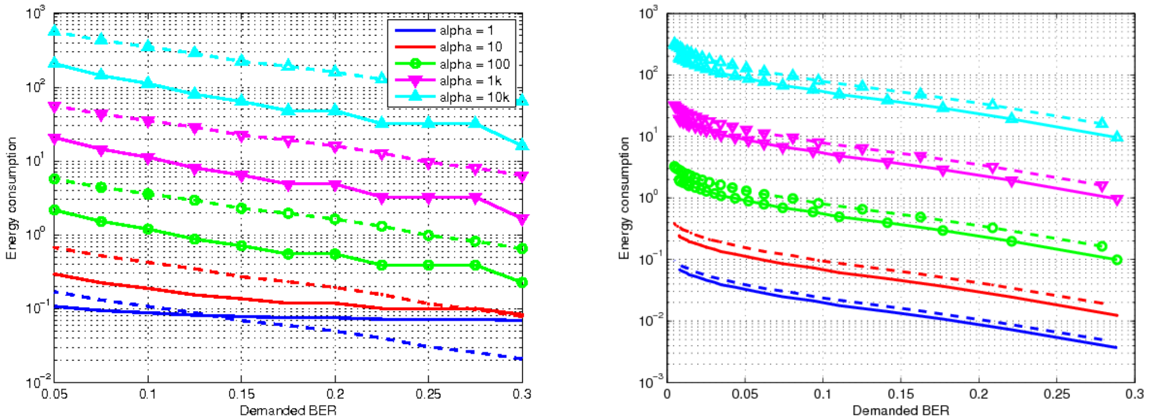
In each scenario, T_m, M_0 and M are assumed to be constant. Therefore, for lower values of T_d where $E_{comP} < E_{initP}$, the proposed algorithm demands more energy. This situation corresponds to $\alpha = 1$ and nearly $\alpha = 10$. When $T_d >> T_m (\alpha = 100,\ 1k$ or $10k)$, then $E_{com} > E_{init}$. Therefore, during the comparisons, E_{comC} and E_{comP} have more prominent roles. Hence, the energy consumption by the first approach has the same variation as that of the conventional algorithm. But the energy saving due to the application of the new algorithm increases by T_d, *e.g.* when the desired BER is 0.05, and the length of communicating message is $T_d = 100 \cdot T_m$, with the new algorithm about 0.4 *watt* will be saved. This parameter arises to 40 *watts* when $T_d = 1e4 \cdot T_m$.

In figure 9-b the second approach of the proposed algorithm is compared with the conventional algorithm. Since in the second approach there is no extra communication load during initialization, the corresponding curves of small T_ds ($\alpha = 1 or 10$) have the same behavior as those of large T_ds ($\alpha = 1k or 10k$). But in the data communication stage, the second approach uses less collaboration nodes which results in less energy consumption. Similar to the first approach, by increasing T_d more energy is saved, but since the second approach is a simplified version of the proposed algorithm which has rather low computational burden, its effectiveness to decrease the energy consumption is lower than that of the first approach.

4. CONCLUSIONS

Several self-optimization ideas to optimize the collaborative data communication algorithms in terms of energy efficiency, reliability and life time are proposed in this paper. The ideas are very flexible and can be implemented in most of WSNs and since they are based on the real-time sensor nodes status and do not impose extra computation or communication load, temporal variation of the nodes and network situation does not have negative effect on their performance.

Since the signal quality is affected by a variety of parameters, the best way to optimize the collaboration would be to evaluate the signal quality of the participating nodes and



(a) Approach I (b) Approach II

Figure 9: Impact of the suggested algorithm on energy efficiency

select the minimum number of nodes to obtain the desired BER. Different metrics including signal quality and energy storage level can be used to select the optimum nodes. Analyses show that the participation of the sensor nodes with the signal quality lower than a minimum threshold in the collaboration has negative effects on the quality of the superimposed signals. Therefore, to reject the low quality nodes from collaboration is advantageous in terms of signal quality and energy saving. Moreover, quality evaluation of the superimposed signals in the destination node guarantees the desired quality of service.

For performance evaluation and comparison, self-optimization ideas are applied to one of the collaborative algorithms in two approaches. The first approach decreases the minimum number of collaborative nodes. The more participating nodes in the node selection stage, the more efficient the optimization would be. In the second approach only a fixed number of extra nodes are used in the node selection stage. Therefore, its complexity is lower than that of the first approach. Since this simplicity is at the expense of lower quality, it is suggested for communication of rather short data messages.

Our investigations proved that the proposed algorithm outperforms its previous versions in terms of energy efficiency and life-time.

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6. REFERENCES

[1] B. Banitalebi, S. Sigg, and M. Beigl. On the feasibility of receive collaboration in wireless sensor networks. In *International symposium on personal, indoor and mobile radio communications*, 2010.

[2] B. Banitalebi, S. Sigg, and M. Beigl. Performance analysis of receive collaboration in tdma-based wireless sensor networks. In *Ubiquitous communication 2010*, 2010.

[3] R. Mudumbai, G. Barriac, and U. Madhow. On the feasibility of distributed beamforming in wireless new vision for distributed embedded systems. In *8th International Symposium on Object-Oriented Real-Time Distributed Computing*, 2005.

[4] R. Mudumbai, D. R. Brown, U. Madhow, and H. V. Poor. Distributed transmit beamforming: Challenges and recent progress. 2009.

[5] H. Ren and M. Meng. Biologically inspired approaches for wireless sensor networks. In *IEEE International Conference on Mechatronics and Automation (Luoyang, Henan*, 2006.

[6] W. Rui, L. Yan, Y. Gangqiang, L. Chaoxia, and P. Q. Swarm. Intelligence for the self-organization of wireless sensor network. In *IEEE Congress on Evolutionary computation*, 2006.

[7] K. Saleem, N. Fisal, S. Hafizah, S.Kamilah, R. Rashid, and Y.Baguda. Self-optimized autonomous routing protocol for wireless sensor networks with cross layer architecture. In *IEEE Symposium on Industrial Electronics & Applications*, 2009.

[8] H. Schmeck. Organic computing - a new vision for distributed embedded systems. In *the 8th International Symposium on Object-Oriented Real-Time Distributed Computing*, 2005.

[9] S. Sigg and M. Beigl. Algorithmic approaches to distributed adaptive transmit beamforming. In *5th International Conference on Intelligent Sensors, Sensor Networks and Information Processing*, 2010.

[10] L. V. Trees. *Detection, Estimation and Modulation theory, Part IV, Optimum array processing*, volume 1st. John Wiley & Sons.

[11] Y. Tu and G. Pottie. Coherent cooperative transmission from multiple adjacent antennas to a distant stationary antenna through awgn channels). In *IEEE 55th Vehicular Technology Conference*, 2002.