A Flexible Non-Orthogonal Software Defined Data Aggregator for IoT Applications

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ABSTRACT
A flexible rate non-orthogonal data aggregator is proposed and discussed for internet of things (IoT) applications. The proposed scheme aggregates the data of several IoT devices before transmission to the cloud for visualization and monitoring. The aggregation scheme is based on non-orthogonal multiplexing and similar to data multiplexing in quadrature amplitude modulation (QAM). Complexity reduced software-defined aggregator and de-aggregator operations are discussed.

Keywords – Data aggregation, Quadrature amplitude modulation (QAM), Internet of things (IoT), non-orthogonal multiplexing

I. INTRODUCTION

Internet of things (IoT) is becoming more prevalent all over the world, wherever internet is within the range of access [1]. Sensors are getting the data from the environment [2], the human being's body [3] and the equipment [4] and send these data usually via wireless access technologies to the remote website, for monitoring and possibly control. Several wireless access technologies such as local WiFi, cellular generations, specifically 5G, LPWAN technologies may provide the required connectivity [5]. Due to the sharp increase in the number of IoT devices in recent years, where it is expected to rise, the role of data aggregators becomes important. Data aggregators combine the collected data from the local IoT devices and send them over internet, and work as an access point, as well.

Data aggregation for IoT has been addressed in several reported researches among them [6], [7]. Importance of data aggregation in IoT is to save the spectral efficiency, to increase the network lifetime by decreasing the number of transmissions, and to add some levels of physical layer security. The reported types of data aggregation for IoT are tree-based, cluster-based and centralized [7].

In this paper, a non-orthogonal data aggregation scheme is proposed and discussed for IoT applications. The proposed approach compresses the data of multiple sensors to one ready symbol to transmit, where it helps in improving the spectral efficiency at the verge of spectrum scarcity. The proposed approach combines the digital information of several sensors based on their importance into one symbol and transmits the symbol over the channel for presentation over the cloud, as it is illustrated in Fig. 1. In development of the proposed aggregator and de-aggregator, we used the efficient structure that was proposed for implementation of hierarchical quadrature amplitude modulation (QAM) [8-11]. The aggregation approach that is proposed for software defined applications, needs small amount of memory and has small computational cost.

The rest of this paper is organized as follows. In section II, the structure of the proposed data aggregator and de-aggregators are given. The implementation cost of the proposed approach is presented in section III. The flexibility of the proposed approach and its performance is discussed in section IV.

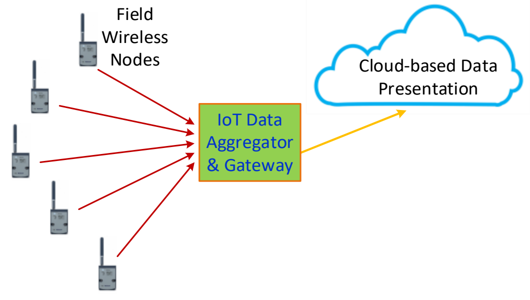

Fig. 1: System model for the proposed data aggregation scheme

II. Implementation of the Proposed Aggregation Scheme

In this section, an implementation routine is discussed for the proposed compressive data aggregator. The proposed data aggregator is based on hierarchical QAM modulation and based on the approach that was discussed in [8,9]. Similar to the scenario that is presented in Fig. 1, each IoT sensor sends its data to the data aggregator that also roles as the gateway of access to the cloud-based data presentation site. These data are stored in the data distributer buffer and sampled to be aggregated as it is illustrated in Fig. 2. The data aggregator module combines the data of different sensors at a constant rate, which is higher than the data rate of each input branch.

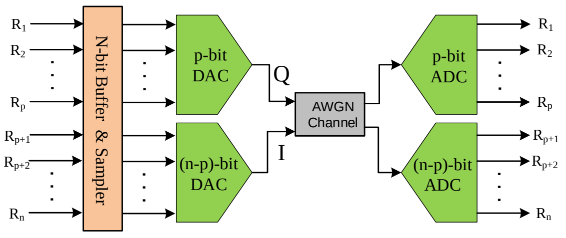

Fig.2: The general structure of the proposed data aggregator and de-aggregator

The sampler's binary output data d_k, k = 1, …, n at transmitter side are combined together with different weights to form the I and the Q components, similar to the formation steps for one symbol of 2^n-QAM [9]. For this purpose, each sub-channel that forms the I and the Q branches are formed by weighted summation of the bipolar binary data d_k that are ±1. Each symbol S is formed as follows:

$$S = I + j\,Q \tag{1}$$

where *I* and *Q* are as follows:

$$Q = \sum_{k=1}^{p} d_k B_k \tag{2}$$

$$I = \sum_{k=1+p}^{n} d_k A_k \tag{3}$$

The A_k for k= 1, …, p and B_k for k = 1+p, …, n are the sub-channel gain profile in combining the binary data branches of the aggregator. Fig. 3, illustrates these unequal gains for aggregator that combines six bits together to form each symbol of the aggregator's output.

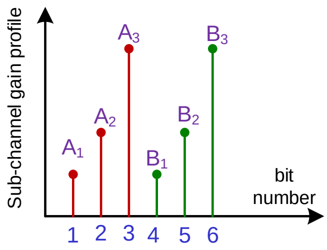

Fig. 3: The sub-channel gain profiles of six-bit data aggregator

It was shown that each combiner in I and Q branch is on analog to digital converter (ADC) [9,10]. Accordingly, the aggregator is one complex ADC (CADC), which is composed of two ADCs for the real and the imaginary terms. One advantage of relating the two ADC structure to a CADC is the simplicity of rotation using complex operations that in software defined system can easily transfer the gains between sub-channels of I and Q branches. The gain transfer allows flexibly shift the capacity among the sub-channels according to the required data rate and performance.

Rigorously, in a corollary [10] it was proved that the optimum maximum likelihood detector for the data d_k are two successive-approximation analog-to-digital converter with the thresholds of decision equal to the sub-channel gain profile, that are A_k and B_k, for all related index values. Accordingly, the de-aggregator consists of two SAR-ADCs. The optimum detector uses successive interference cancellation (SIC) algorithm for detection of each bit based on the order of the data in aggregation process and from high gain to low gain. For optimization algorithm additive white Gaussian noise (AWGN) was assumed [10].

III. Computational Complexity and the Required Storage

The proposed aggregation algorithm has low computational complexity and in comparison, to table look-up needs much less memory for storage. In this section the complexity of the proposed aggregator is discussed.

According to (1) and (2), the n-bit data aggregator with p-bit in Q branch and (n-p)-bit in I branch needs n real multiplications and n-2 real additions. The de-aggregation process also needs n comparators and n-2 real subtractions to use SIC.

The proposed approach needs n real memory spaces for storage of n gains of the sub-channel gain profile. Because it needs to be able to manage all of the possible number of bits from 3 bits and up of data per symbol S, then the sub-channel gain profiles of these cases have to be considered in storage count. Accordingly, the total number of required memory spaces for the aggregator and the de-aggregator is:

$$N_P = 3 + 4 + \cdots + n = n(n+1)/2 - 3 \quad (4)$$

In comparison, the table look-up approach needs 3.2^n memories for aggregating any n bits of data. Accordingly, for all of the possible 3-bit and up it needs a large amount of storages according to (5).

$$N_T = 3(2^3 + 2^4 + \cdots + 2^n) = 3(2^{n+1} - 8) \quad (5)$$

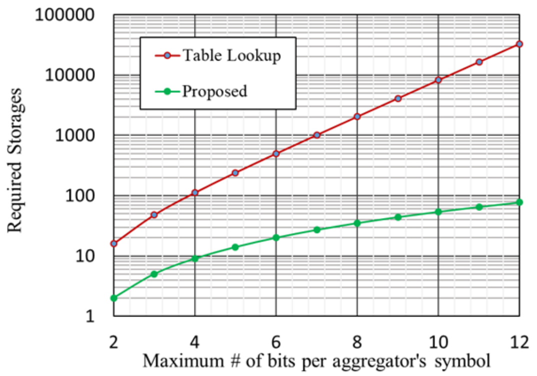

Fig. 4: Comparison between the required storages of the proposed approach and table look-up

Fig. 4, illustrates the required memories of these two approaches in logarithmic scale. According to this graph the proposed approach needs much less memory spaces for the software defined system.

IV. Performance Evaluation

The proposed data aggregator in this paper is flexible and it can relatively change the capacity and the maximum possible rate of each sub-channel to allow the IoT sensor that needs higher data rate to transmit, accordingly. For this purpose, we discuss the effect of scaling and rotation on bit error rate and the sub-channel capacity.

The exact bit error probability of each subchannel was analytically discussed in [12, where it can be used for calculation of the capacity of each sub-channel of the aggregated data. With P_k, the average bit error rate of the sub-channel number k in the presence of AWGN, the capacity bound of sub-channel in the presence of AWGN is according to (6).

$$C_k = 1 + P_k \, Log_{10}(P_k) + (1 - P_k) \, Log_{10}(1 - P_k) \quad (6)$$

Fig. 5 illustrates the bit error probability for 8-bit aggregation per symbol in AWGN channel based on simulations and analytical approach, where both perfectly support each other.

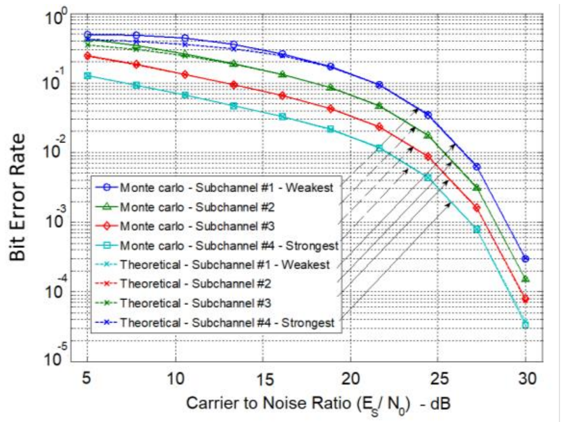

Fig. 5: Exact bit error probability of different sub-channels of 256-QAM, based on simulations and analysis

Rotation and scaling are two possible approaches to change the sub-channel gain profile and accordingly change the sub-channel's capacity bound and then data rate. It is important to mention that this change affects the capacity bound of the other sub-channels, due to non-orthogonal, coexisting interference from the other sub-channels.

Fig. 6, illustrates the sub-channel gain profile of 6-bit aggregator per symbol, before and after 10-degree rotation of the forming vector $V = A_1 + j B_1$. The related bit error rate of the rotation is presented in Fig. 7. According to this figure, even 10-degree rotation of the weakest sub-channel results in tangible changes in bit error rate of the other sub-channels. The reason for rotation of the weakest sub-channels (related to the data bit #1 and #4) is to apply the least interference on other sub-channels. This theoretical experience clearly prove that the proposed data aggregation scheme can flexibly shift the capacity and accordingly the data rate between the sub-channels that each is assigned to one sensor's data. The simple operation such as rotation can be done with low computational load in software defined platform in IoT data aggregator / gateway unit.

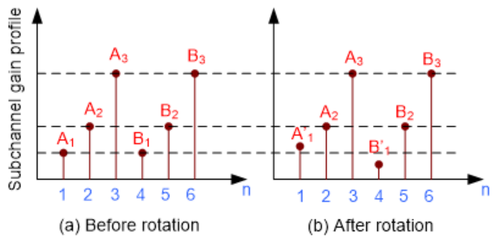

Fig. 6: The sub-channel gain profile of 6-bit data aggregator before and after 10-degree rotation of the vector that the weakest sub-channels.

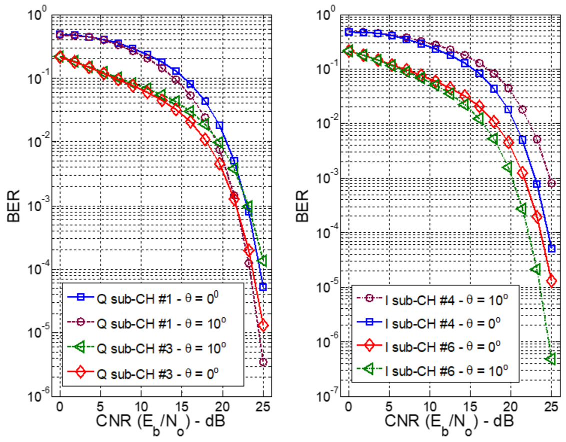

Fig. 7: Bit error rate of 6-bit aggregator in AWGN before and after 10 degrees rotation of the weakest sub-channel. The graph shows the bit error rate versus Carrier to Noise ratio (CNR) in dB

To investigate the effect of scaling, the gain of the weakest sub-channels (related to the data bits #1 and #4) scaled up by multiplying them with constant factor 1.2. Fig. 8 illustrates the result of this investigation. According to these results, similar to rotation, scaling also improved the capacity of the amplified sub-channels and it decreases the capacity of the other sub-channels due to increase in co-channel interference level.

V. Conclusion

A flexible and low-complexity data aggregator based on hierarchical quadrature amplitude modulation is discussed for internet of things (IoT) applications. The proposed approach needs relatively small amount of memory space. It is shown that by simple operations such as rotation and scaling it is possible to change the data rate by changing the error rate of the sub-channels. The simulation results support the potential of flexible capacity exchange among data of different IoT nodes.

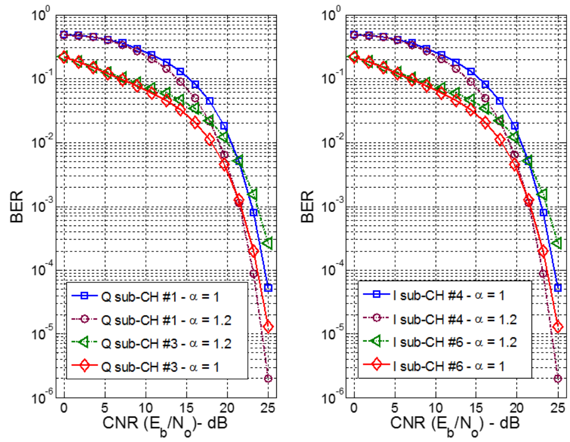

Fig. 8: The bit error rate of the selected sub-channels of 6-bit data aggregator before and after scaling of the weakest sub-channels (sub-channels #1 and #4).

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