Data optimization for communication between wireless IoT devices and Cloud platforms in production process

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Abstract. The article deals with optimization of input data for wireless IoT devices with database handled by cloud framework. Tested hardware consists of ESP32 board with Wi-Fi technology support (Thinger.IO cloud platform) and Sensor Tag development boards with integrated sensors and Bluetooth connection communicating with IBM Watson IoT framework. The new idea is how to send optimized measured data to IoT platform which is limited to one message per second usually. We propose two separate approaches for input data: accumulation data in IoT device to multi-value packet and noise elimination solved by advanced interpolation (Kalman filter). Both principles can be combined to reduce noise and increase of data frequency stored in cloud platform for next knowledge datamining. Data accumulation can be used for machine or product vibration analyses (acceleration data packed during 1 second) in cloud platform. Interpolated data can remove noise from actual product operational speed (gyroscope/magnetometer corrected value) to reduction false alarm messages in cloud framework.

Keywords: wireless technologies, IoT devices, clouds platforms, sensors.

1 Introduction to IoT devices

IoT systems or otherwise called “Internet of Things”, we can designate as a technique and informatics connecting built-in devices to the internet. Usually this connection is between the wireless device and internet and brings new possibilities of interaction too, such as data collection, analysis and then processing. Their use can be applied by means of measurement or monitoring sensors in industry environment or households. They can also be used for tracking process, its movement and position of technical or industrial means or goods. In short, the use of IoT systems is now useful, because data processing is easier or more effective. The biggest problem is the different existing standards for communication of the given devices, which are distinguished by producer groups. The list below is currently the most well-known organizations in terms of providing IoT systems.

The most well-known organizations of IoT systems include: Open consortium for the connection (Intel, Dell, Samsung, Broadcom, etc.), AllSeen Alliance (LG, Cisco, Microsoft, Qualcomm, Sharp, etc.),Industrial Internet Consortium and Turn off the OGC web sensor.

The current IoT systems can define development trends at: The Industrial Internet of Things (Industrial Internet), Consumer Internet of Things for households.

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Some decentralized systems in industry are suitable to own local server only and there is no need to use Cloud solutions. This is so-called Fog computing, where devices communicate with each other (P2P). Fog Computing is thus locally isolated Cloud. The calculation together with local data being centralized, e.g. in companies with local servers data are then evaluated by them. This makes it possible to achieve better manoeuvrability, reliability, faster server responses, and cost reduction. This approach is mainly used in the industry where an emphasis is on reliability and system responsiveness. Results and processing can then be sent to Cloud systems where they can be centred, for example, as a backup in the event of a local outage server. The experiments with clouds platforms and IoT devices for industry were published in many indexed articles. Some research in cloud data processing of vibration was described in [1], industrial management of IoT devices [2], fog computing for industrial devices [3], machine learning algorithms implementation into embedded systems [4], services model for industrial IoT [5], description of smart gateway for home internet of things [6], IoT and transparent computing [7], smart manufacturing with internet of things [8], improving services of IoT [9].

2 Wireless technologies used in IoT devices

Wireless connection segment is very reach to technologies and can be divided according communication distance, bandwidth and power consumption. The most used technologies which can be used for IoT segment are described in next section.

Wi-Fi (Wireless Fidelity), currently, it is the most common Wi-Fi standard used in home and in many 802.11n enterprises, which offers serious performance in the range of hundreds of megabits per second, which is good for file transfer but can be too demanding for data processing in IoT applications and subsequent transfers. The main disadvantage is higher power consumption [10].

Bluetooth Low Energy (BLE) IoT uses a special Bluetooth type, called Bluetooth Low-Energy or Bluetooth Smart. This means that this type is primarily used where there is no need to transmit a large amount of data, and it also says that the device does not require a large built-in battery for communication from the end device. However, Smart / BLE is not really designed for file transfer and is more suitable for small parts of data. The main disadvantage is that we need some bridge device to send data to ethernet network [11], [12].

ZigBee has traditionally higher share in industrial environments. ZigBee PRO and ZigBee Remote Control (RF4CE) based on IEEE802.15.4, a wireless industrial networking technology operating in 2.4GHz targeting applications that require relatively low data exchange at low data.

6LowPan is a network protocol that defines encapsulation mechanisms and header compression. The standard has freedom of bandwidth and physical layer and can also be used on multiple communication platforms, including Ethernet, Wi-Fi, Bluetooth and sub-1GHz.

SigFox provides the lowest energy-consumption device-to-cloud. The Cloud is managed by the provider, and the user can connect their IoT sensor within any coverage area.

LoraWAN (Lora Network) is more open standard for creating IoT network, any company can create your own networks with gateways and connect its sensors.

The next protocols which can be used in IoT for wireless communication are **Thread**, **Z-Wave**.

The short overview about these connections technologies with some basic parameters is shown in Table 1.

Table 1. Parameters of wireless technologies usable for IoT devices.

Technology	Distance [m]	Bandwidth [kB]	Power (3.3V) [mA]
Wi-Fi (ESP32)	50-100 m	150-200Mb/s	75
Bluetooth LE (ST)	>100 m	0.27 Mb/s	10
ZigBee	~100 m	250 Kb/s	~15
Lora WAN	∞	< 10 Kb/s	~20
SigFox	∞	100 b/s	10 years

3 IoT Device used for experiment

We selected wireless technology according available devices: ESP32 includes Wi-Fi technology (802.11b/g/n) and two SensorTag devices provides Bluetooth 4.0 subclass Bluetooth Low Energy (BLE).

We created two main testing stands used in next experiments:

- Solution with Bluetooth wireless (BLE) connection and external data mining to Cloud external server (IBM Watson IoT).
- Solution with Wi-Fi connection and data storage to fog cloud in local server (Thinger IO).

3.1 SensorTag wireless connection

The Sensor Tag provides data from 7 sensors: accelerometer, gyroscope, magnetometer, microphone, local and remote (infrared) temperature sensor. The data bridge between Bluetooth connection and internet is Android tablet which push data to IBM Watson Server. Principle scheme of dataflow can be seen on the **Figure 1**.

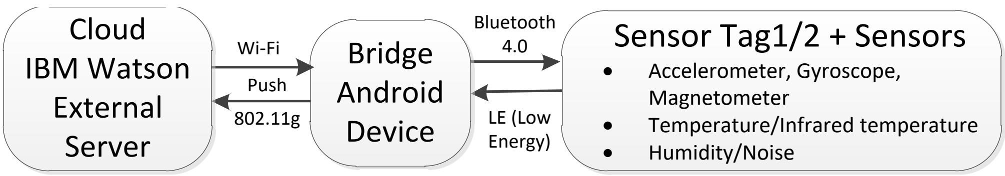

Fig. 1. Diagram of SensorTag IoT wireless connection.

Bluetooth connection by LE (Low Energy) provides low power consumption and is viable to use for battery powered devices. The control processor is 8bit MCU with low consumption too. The main disadvantage is installed bridge BLE/Wifi which must have high reliability.

3.2 ESP32 wireless connection

The ESP32 provides internal Wi-Fi connection in board but doesn’t offer any integrated sensor. We connected sensor for spatial data 10 DOF sensor DMU6050 (accelerometer, gyroscope, magnetometer, pressure) and combined sensor acquisition of humidity, environment temperature DHT11 and TOF laser distance sensor VL53L0X. Principle scheme of dataflow can be seen on the **Figure 2**.

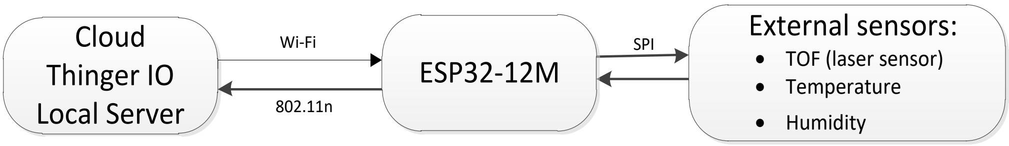

Fig. 2. Diagram of ESP32 IoT wireless connection.

The device uses 16bit control processor with 160 MHz frequency and with Wi-Fi connection drain about 80 mA, which is not very effective for battery power. Computing performance provides better platform for computing intensive algorithms, as for example Kalman filter. The main disadvantages are external sensors and higher power consumption.

3.3 Used IoT devices

We tested both devices using USB hub instead of battery, because we need reliable getting data in long interval. The used devices for data mining from automation line environment are shown on the **Figure 3**.

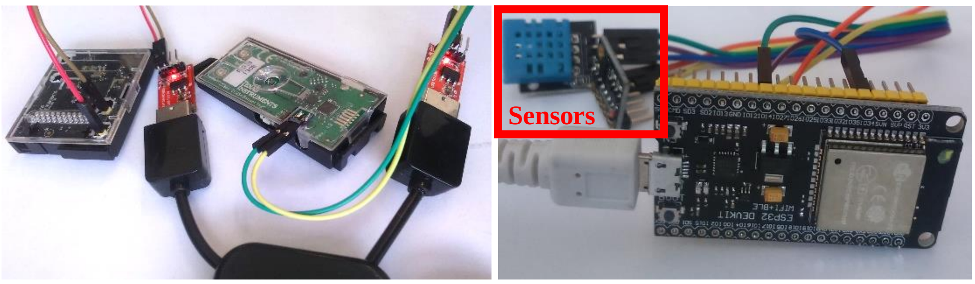

Fig. 3. Tested hardware, SensorTag1/2 (left), ESP32 (right) with external sensors.

4 Data input improvement in IoT Cloud platforms

IoT cloud platform for data store is limited to get data continuously, because we assume that there are connected too many devices (it is not possible to process real-time data). The communication interval for sensors is usually set to minimum 1 second interval. The article introduces two principles, the first to increase data acquiring frequency for input data and second for input data interpolation.

We assume two main methods to solve data delay on IoT platforms:

- The main principle of data storing in package is based on collecting data during waiting interval and send more data in one package to IoT server platform, which must these data parsing to group of values (necessary open-source IoT device).
- The next problem is input data noise which can be interpolated and send to cloud filtered value in 1 second interval (data post processing plugins with extended filters).

The detailed description of both methods of improvement for input data is described in next two subchapters.

4.1 Data accumulation

Basic principle is acquiring how many data we can compress to one package during 1 second period. It depends mainly on how precise we need send value. For temperature we only need 8bit value (256). For position sensors is suitable use 16bit value (65 536). The examples of grouping value in one packet can be seen on the **Figure 4.** Data frame collects values during selected delay (1 second), when interrupt start program count number of collected values and write on the end of frame.

Serialized data during Cloud send interval interval

	Data1		Data2		Data3		Data4		Data5		Count

Fig. 4. Data frame with accumulated values during waiting interval.

4.2 Data interpolation by Kalman filter

If we need more values that IoT Cloud can receive we need some methods to estimate intermediate values. There exist many methods based on averaging last values, but in IoT we don't have enough of these values for simple prediction. The most suitable method for small set of values (one value per second) is Kalman filter or Extended Kalman filter [13], because we can include different dynamics for specific sensor value [14].

The basic principle of implementation math to Arduino IoT 8bit MCU is described by equation (1).

$$\hat{X}_k = \mathrm{K}_k \cdot Z_k + (1 - K_k) \cdot \hat{K}_{k-1} \tag{1}$$

where:

$\hat{X}_k$ – current estimation
K_k – Kalman gain
Z_k – measured value
$\hat{K}_{k-1}$ – previous estimation

For acquiring values we need to do two steps: first for prediction and second for correction. The first step is time update (prediction) and we can acquire it by equation (2).

$$\overline{\hat{X}_k} = A \cdot \hat{X}_{k-1} + B \cdot u_k\,; \quad \overline{P_k} = A \cdot P_{k-1} \cdot A^T + Q \tag{2}$$

where:

A, B, H – form matrices from model
u_k – control signal

The second step is measurement update (correction) and it can be acquired by equation (3).

$$\mathrm{K}_k = \overline{P_k} \cdot H^T (H \cdot \overline{P_k} \cdot H^T + R)^{-1}\,; \hat{X}_k = \overline{\hat{X}_k} + \mathrm{K}_k\left(z_k - H \cdot \overline{\hat{X}_k}\right); P_k = (1 - K_k \cdot H)\overline{P_k} \tag{3}$$

where:

R, Q – noise covariance's variables

We assume simplified plant model of device signal which can be described according equation (4).

$$X_k = X_{k-1} + \mathrm{w}_k \; ; z_k = X_k + v_k \tag{4}$$

where:

- w_k – mean
- v_k – standard deviation
- X_k – our signal values

This filter was implemented for sensors with noise, for example accelerometer, gyroscope and magnetometer.

5 Implementation to IoT devices and Cloud platforms

The first implementation assumes data accumulation. The SensorTag data is collected by Android tablet in laboratory and push it to IBM Watson IoT Cloud (device list, data bandwidth/timeline) and stores data in JSON standard format (cloud side) as it is shown on the **Figure 4**.

The acquired data is processed by parsing with integrated “Node Red” application to modify data (split) and then is send back to IBM Watson and stored to Cloudant no SQL database (**Figure 5**).

The second implementation modify input data in IoT device by Kalman filter to reduce noise from accelerometer if we want get only position and not the vibration from acquired signal. Signal is filtered inside of 16bit MCU ESP32 by external library function (**Figure 7**).

Example of dashboard for second platform ESP32 with Wi-Fi connection and Thinger IO is shown on the **Figure 8**.

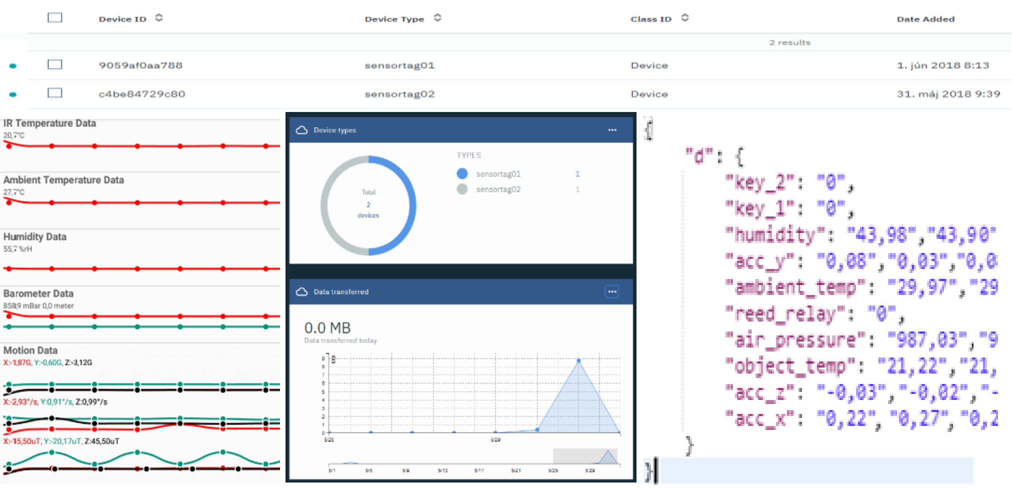

Fig. 4. Data acquisition from SensorTag (left) represented in IBM Watson IoT Cloud/Json (right).

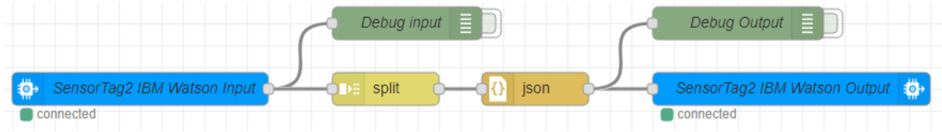

Fig. 5. Data flow modified by Node Red application to split each value.

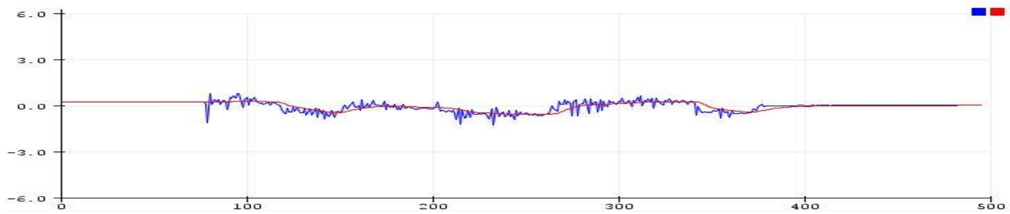

Fig. 7. Data from accelerometer aY (blue) fitered by Kalman filter implementation (red).

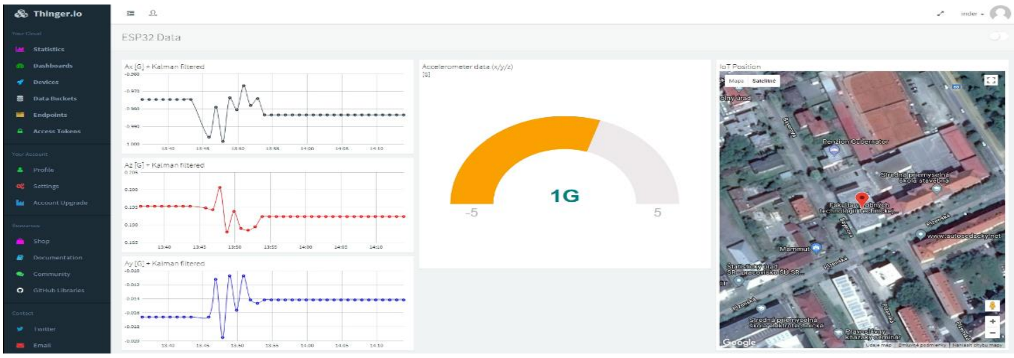

Fig. 8. Filtered data acquisition from accelerometer (aX, aY, aZ) by ESP32 stored in Thinger IO.

6 Conclusion

The paper deals with optimization of input data for wireless IoT devices, for example in monitoring production process. The new approach is extending input data by accumulation to multi-value packet and data interpolation with advanced filters (Kalman Filter) used to noise reduction. We used for experiment two wireless platforms, the first with Bluetooth 4.0 low energy (BLE) and second with standard Wi-Fi (802.11n) connection. Testing data from both platforms were acquired from 7 sensors (accelerometer, gyroscope, magnetometer, temperature, humidity, pressure and microphone). The next experiment confirms usability of Kalman filter inside MCU to interpolate values from accelerometers. Both methods can optimize data for IoT platforms. Accumulation of data can increase precision of measurement if we need, for example acquire vibration, and Kalman Filter can eliminate noise from movement trajectory or speed of rotation in construction nodes [15]. The main limitation of used Bluetooth IoT devices (Sensor Tag) is necessity of BLE/Wi-Fi bridge, which decreases reliability of solution. Disadvantage of IoT based on ESP32 is external sensor connection, which can may affect interference from environment. The next research will be aimed to extend experiments with sensors to Sigfox and

Lora-Wan connection and testing other open source cloud platforms (Kaa IoT, ThingSpeak, thingsboard.io). The next works can be implementation some prediction of data for day, week or month, which can be used later for production system predictive maintenance.

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