Powering the IoT Through Embedded Machine Learning and LoRa

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***Abstract*—The Internet of Things (IoT) technology is rapidly changing the way we live and the number of connected devices are increasing at an exponential pace. However, two key challenges are the battery life for off-grid IoT applications and the ability of edge devices to communicate over long range. Raw data transmission poses as a very power hungry activity for any device. The conventional cellular wide area networks are power-hungry and incompatible for battery-operated IoT devices. There is a need for low-power edge computing devices that reduce the transmission payload and integrate Low-Power Wide-Area Network (LPWAN) technologies, which offer a wide range connectivity while still providing a long battery life. One of the most promising LPWAN technologies today is LoRa. In this paper, we present a solution that employs machine learning on the edge device and performs low power transmission through LoRa. We demonstrate the use case of our solution through a field trial conducted in China for sow activity classification. By implementing embedded machine learning with LoRa, we could compress the transmitted data by 512 times and extend the battery life by three times. A very low energy expenditure of 5.1 mJ per classification result is achieved.**

***Keywords*—Machine learning, IoT, LoRa, LPWAN, Edge Computing**

I. Introduction

The Internet of Things (IoT) is burgeoning [1]. From intelligent fridges [2] to wearables [3] [4], there is an increased penetration of intelligent and connected edge devices in our day to day lives. IoT based devices are poised for an exponential growth to almost 28 billion in number by 2021 [1].

The sustained growth and increasing ubiquity of IoT is hinged upon a seamless integration with the application environment. The ability of IoT to power themselves over extended duration without the need to recharge is an important aspect of this desired integration [5]. At the same time, the demand for IoT in applications of increasing complexity requires data transmission, storage and processing capabilities which are all power intensive functions. For data processing a popular strategy has been the use of cloud [6] for data analysis needs, wherein raw data is transmitted to the cloud for processing and analysis. However, the transmission of a large volume of data requires the need for a continuous power source or frequent charging [7], limiting the scope of cloud based IoT. Additionally, the maintenance of cloud based infrastructure is an expensive endeavor [8] which could have significant economic implications for consumer devices.

Furthermore, the IoT applications increasingly need to transmit data over long distances. Growth in IoT in areas such as traffic monitoring, soil condition tracking and animal health monitoring would all require a large geographical spread of sensors. Thus, the ability to transmit data over long distances while maintaining power efficiency will be an important factor in IoT devices. Such off-grid IoT devices will also require edge processing to reduce the need for high transmission bandwidth and dependency on cloud as a data analysis platform.

In this regard, efficient use of data compression and local data analysis to reduce the required transmission bandwidth is a viable strategy which could be evolved with the use of long-range small-bandwidth protocols [3], [9], [11] and [12]. One such protocol that is starting to gain importance is LoRa (a long range low power wireless transmission protocol) [13]. High bandwidth protocols like 2G/3G/4G are power intensive and protocols like Bluetooth/ZigBee are unable to communicate over long distances (~kilometers). As shown in Fig. 1. LoRa is located at the junction of low power and long range.

In this paper the key novelties are that,

- We demonstrate the use of LoRa coupled with machine learning on an embedded system (Edge Device) with an analysis on various factors affecting the battery life.
- We present the results of a field trial for animal health monitoring, conducted on animals at a farm in Jiading District, Shanghai, China.

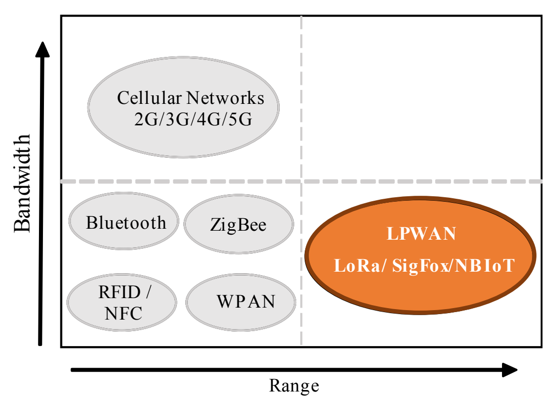

Fig. 1. Bandwidth requirement v/s range capability of various wireless protocols

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- By performing edge processing we increase the battery life from 13 days to 39 days. We, further, show that it is possible to extend it to 331 days by incorporating different optimizations on the sensor node.

The rest of the paper is organized as follows. Section II talks about the different works that have explored edge computing and LoRa protocol. Section III describes the system architecture and our choice of hardware while section IV presents methodology for activity classification task. In section V, we present the results of our field trials with special emphasis on power dissipation and concomitant battery life. In section VI, we provide some insight into our field trial. Section VII describes direction of our future and we conclude with section VIII.

II. Related Works

A number of IoT applications exist where the edge nodes are simple sensor motes that collect data and transfer it to servers through gateways. In [14] a sensor node platform called Intel Mote uses an ARM7TDMI core and a CMOS Bluetooth radio. The maximum range they could attain was 100 m.

The authors built on their work in [15] to produce IMote2 which achieves a 48x reduction in energy consumption by performing FFT analysis on edge sensor node. The approach of performing Edge Processing has become increasingly popular due to its power savings. It has been explored in the last few years in several works [10], [16], [17] and [36].

Such integrated sensor applications are an obvious prey to storage, transmission and security problems. Machine learning is being done on the edge nodes to save on the transmission bandwidth and power. Reference [18] provides a theoretical framework for applying machine learning to the IoT. Most literature only mentions the isolated energy requirements of the edge device without considering those of communication protocols involved.

The communication protocol is a power-hungry component. There have been works [19], [20] that have evaluated the power performance for wireless protocols like 3G, 4G, Bluetooth, ZigBee etc. The short range and power consumption for such protocols (Fig. 1) does not fit the requirements for most IoT applications. Therefore, we focus on integrating LoRa. There has been research with evaluation and application of LoRa in isolation. [21], [22] and [23].

Many works have reported the performance of LoRaWAN network for different application scenarios like river monitoring [24], object tracking [25], cattle tracking [26], sailing monitoring [27] and industrial wireless networks [11]. In [12], Augustin et al., (2016) provided a comprehensive analysis of LoRa's PHY and MAC layers operating in the EU band (868 MHz). In [28], the received signal strength indicator (RSSI) and delay of the data transmission were considered for 915 MHz ISM band operating in Indonesia. In [29], the performance of LoRa was studied under NLOS indoor environment for human-centric applications. In [30], the robustness of the LoRa communication link against the Doppler frequency shift was investigated. It was observed that for low-speed mobility scenarios (below 25 km/h), the communication is sufficiently reliable and thus LoRaWAN can be utilized for a variety of applications including livestock monitoring.

Finally, in [31] [32] sow-activity classification is done using machine learning. Although they report a battery life of 4 months their running current is reported to be 50 mA. They also do not tackle the long-range transmission issue in their paper. It is focused only on the machine learning techniques that they apply to sow classification. We on the other hand are not application constrained in our approach.

To the best of our knowledge there isn't any work that evaluates the power requirements for a system that combines the low power protocol LoRa with embedded machine learning. We identify this as a necessary requirement for the upcoming IoT revolution and propose a solution and present the field testing results.

III. System Architecture

The primary goal of this work is to make use of low-power embedded machine learning at the edge in a LoRaWAN network. Fig. 2 shows the network architecture of a typical LoRaWAN network. The end-device captures the raw sensor data, and performs data classification directly on the sensor node, thereby reducing the data transmission bandwidth and latency. End-devices communicate with the nearest gateways in a star topology and the gateways are connected to the network server through an IP connection. The gateways forward messages from the LoRa end-devices to the network server. The communication link is bidirectional. We additionally use the downlink for over-the-air activation of different operating modes on the device. The network server acts as the master network controller and manages the data rate of each end-device through automatic data rate (ADR) control mechanism. An application server helps in data visualization and alerts can be sent to the end-user through cellular networks. All the network parameters conform to the LoRaWAN specifications [34] framed by the LoRa Alliance.

A. Choice of Embedded Hardware

We demonstrate the use of LoRaWAN for activity classification of sows in an animal farm located in Jiading District, Shanghai, China. The network was implemented to operate in China and conforms with the LoRaWAN 1.0.2 Regional Parameters [35] set up by the LoRa Alliance for operation in CN 470-510 MHz band. 'Class A' LoRa devices were chosen as they are the least power consuming and allow bidirectional link with the gateway. Fig. 3(a) shows the block diagram of custom designed LoRa end-device consisting of an energy-efficient ARM Cortex - M0+ processor, Semtech

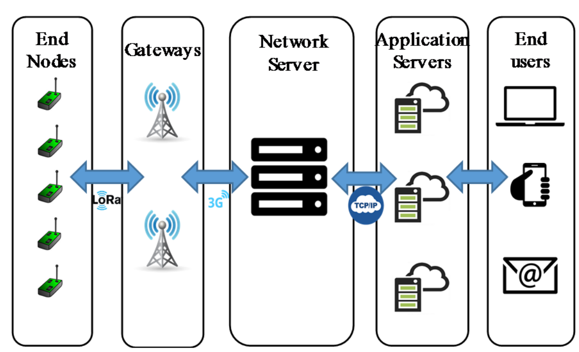

Fig. 2. Typical LoRaWAN System architecture

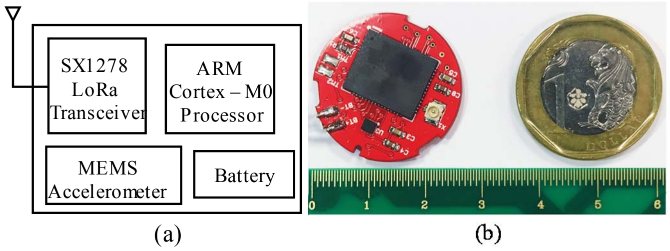

Fig. 3. Block diagram of PCB used for activity classification

SX1278 LoRa transceiver [38], and a low-power MEMS accelerometer. The device (Fig. 3(b)) was attached to the sow's ear. The stringent area requirements were met and the complete solution was realized with a circular PCB of 2.6 cm diameter, through careful selection of components. A helical antenna operating at 470 MHz was connected to the PCB using an IPEX micro coaxial connector. The device was powered by a 1000 mAh capacity battery. The end nodes communicate with a LoRa gateway powered by Semtech SX1301 baseband processor which can handle 8 different LoRa devices simultaneously. Raspberry Pi integrated with the gateway acts as the network server and a dashboard visualizes the analyzed data.

IV. Activity Classification Methodology

Activity classification happens on the end device. It can be performed by using various algorithms, the choice of which depends upon individual use case. We focus on k-nearest neighbors (kNN) algorithm for activity classification mainly because of its ease and simplicity of implementation and high enough accuracy of 96.2% (refer section VI for details) for application under consideration. The classification process involves accumulating programmable number of samples from the accelerometer (we accumulate N samples such that N is sufficient to capture the activity signature). The collected samples are then used to extract a set of commonly used features such as mean, co-variance, wavelets, moments etc. The extracted feature vector is then fed to kNN as a d-dimensional point, we find out the minimum distance of this point from a predefined set of points each belonging to a specific class extracted during the training phase.

We configured embedded implementation for specific subtype of kNN where we represent each class cluster by a single template point given by the centroid of all training points of that class. The template for each class then serves as the only point from which distance needs to be computed for kNN, rendering the choice of k=1 for our implementation. Use of template points instead of all training sample points also helps in better generalization. In conventional kNN, with a small k and a large number of training sample points, the test points in the vicinity of a few outliers or mislablled training points would be wrongly classified. With the centroid representation of clusters, minority outliers and mislabeled samples get very less weightage.

Fig. 4 shows the flow of data through various stages of processing. The device is switched to a mode where it only extracts the features and transmits them through LoRa. We use a camera setup monitoring the animal when the device is transmitting the features. The received features from the device are then labelled with activity, manually, with the help of

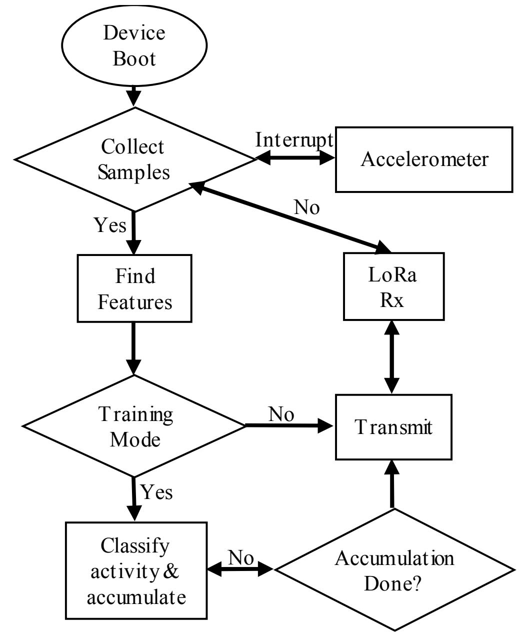

Fig. 4. Flowchart – Data capture and processing stages

recorded video, according to their timestamps. We collect enough data during the training phase to have, roughly, equal number of data points for each activity to avoid any bias.

During testing, each point (feature extracted from N samples of accelerometer) is fed to the algorithm (one d-dimensional point at a time) and the final class is then transmitted via LoRa. With accelerometer sampling frequency of 'f' Hz, we collect 3N (N samples for each of the X, Y & Z axes) acceleration values in T (=N/f) seconds with each acceleration value being a 8 bit signed integer. If we were to transmit this data as is typically done in most of IoT devices [14] it amounts to 3N bytes of data every T secs. After classification this data is now compressed to just 1 byte as the class to which the data belongs to. Also 1 byte can be used to represent 256 different classes hence further compression can be achieved by using just $\log_2 C$ bits to represent C different classes. Hence we achieve an effective compression of $(8*3N/\log_2 C)$ times, removing the redundancy from the accelerometer samples and converting it to meaningful data on the edge device itself.

Traditional data compression techniques necessitate the use of a server infrastructure to uncompress the data and perform classification, thereby incurring additional development and maintenance costs. By performing processing-based compression we not only save on these costs but also enable applications that require time critical alerts for specific animal activity patterns. For traditional data compression approaches, activity information is decoded only at server and hence can't cater to real-time alerts.

V. Results

A. Choice of Parameters

The 'always-on' accelerometer sampling at f=50 Hz consumes less than 10 µA current. The microcontroller unit (MCU)-ARM Cortex-M0+ and RF module SX1278 consume less than 30 µA and 1.5 µA in idle mode, respectively [37], [38].

From measurement results, we found that the entire module consumes 52 mA, 30 mA and 1 mA current in Transmit, Receive and Data Capture and Processing states respectively.

For each LoRa communication there is one Transmit window of 23-128 ms (for TX of payload of 1-51 bytes) and two Receive windows of 23 ms (for RX1) and 192 ms (for RX2). In LoRa, receive windows serve dual purpose of acknowledgements and transmitting messages from gateway to end device. This can be useful for updating device parameters over the air. In case of poor connectivity, the Spreading Factor [34] of LoRa increases resulting in a wider Transmission Window.

We designed the system with following parameters: C=8 potential classes (of which, we only use 2 classes and 5 classes for sow and human activity respectively), Accelerometer sampling frequency f=50 Hz, MCU CLK frequency=2 MHz Accelerometer Sample = 8-bit signed integer, N=64 samples. The following 3 Cases are explored – 1) 1 classification result (3 bits) per TX. 2) 136 classification results per TX with MCU always in MCU mode and 3) 136 classification results per TX with Standby MCU put to low power stop mode when idle. LoRa nodes are chosen to operate within 471.5 MHz to 473.1 MHz with a transmit power of +10dBm. The channel spacing and bandwidth are 200 kHz and 125kHz respectively [35].

B. Battery Life and Energy per Classification

1) Case 1

In this case, we consider performing just a single classification over 64 accelerometer samples and transmitting it in a single byte.

The current profile for one LoRa transmission can be seen in Fig. 5(a). The accelerometer operating at 50 Hz processes a window of N=64 samples in T=1.28 s. The data processing is

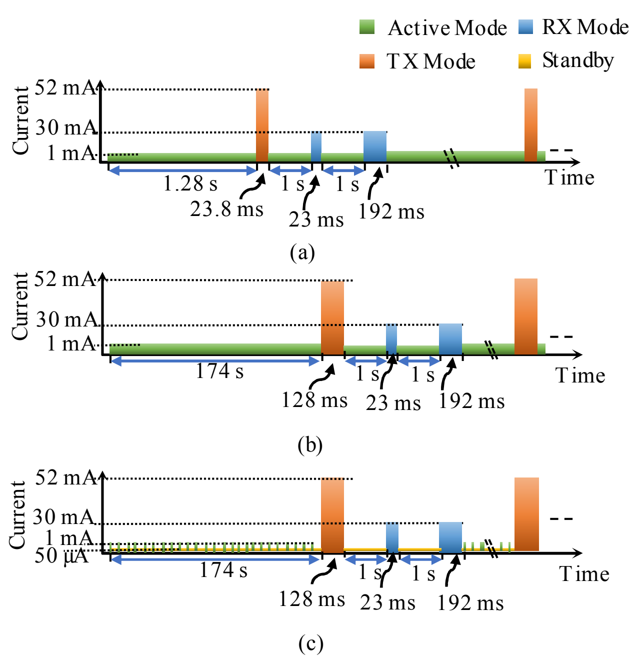

Fig. 5. Current Profile for TX, RX, Active and Standby modes for the 3 cases in Section V-B

Table I. Current Consumption, Time Duration and Average Current for various modes of operation

device mode	I (µA)	Case 1		Case 2		Case 3	
		TX 1 class every 1.28 sec		*TX 136 classes every 176 sec (MCU always in active mode)*		*TX 136 classes every 176 sec (MCU in stop mode when idle)*	
		Time (ms)	*Avg I (µA)*	*Time (ms)*	*Avg I (µA)*	*Time (ms)*	*Avg I (µA)*
TX	52e3	23.8	352	128	37.7	128	37.73
RX	30e3	215	1833	215	36.6	215	36.56
Active	1	3280	932	176e3	998.1	345	1.96
Stop	50	0	0	0	0	1757e2	49.81
Energy per Classification		14.76 mJ		5.1 mJ		0.597 mJ	

completed within these 1.28 seconds. For each transmission, we compute the average current as the current for that mode divided by the total time (time taken for data processing plus time for two RX windows along with one TX window) taken by all the modes together.

From Table I and Fig. 6(a) the average current for TX and RX together contribute to more than 85% of the total average current. The transmission time for 14 bytes (1 byte payload + 13 bytes header) is 23.8 ms. Case 1 is considered to demonstrate the need for data processing before a LoRa transmission. The total average current for this case comes out to be 3.12 mA. From Table I we see that Case 1 has an energy expenditure of 14.76 mJ per classification. A 1000 mAh battery will only last for 13 days in this case (Fig. 7).

2) Case 2

To mitigate the power concerns, we combine 136 classification results (with each classification being performed over 64 samples. (3 bits/classification * 136)/8 = 51 bytes). The CN 470-510 MHz band allows for a maximum packet size of 64 bytes per TX. With LoRa TX supporting a maximum payload of 51 bytes (+13 bytes for LoRa header) and each classification label being represented as a 3-bit number we are able to club 136 classifications.

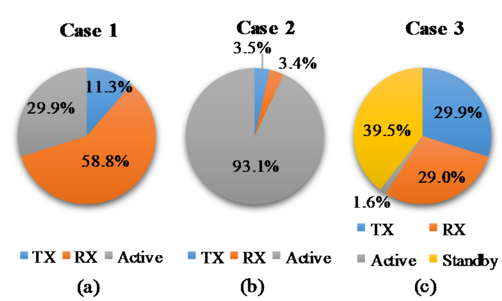

Fig. 6. Pie Charts of average current contribution of TX, RX, Active and Standby modes for the 3 cases in Section V-B

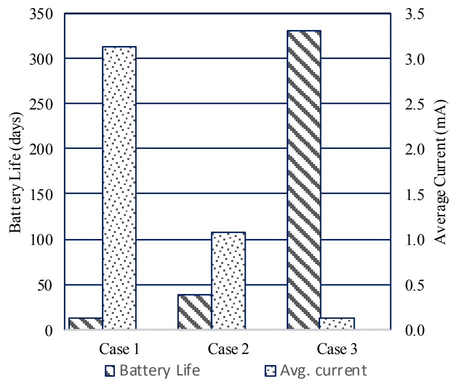

Fig. 7. Battery Life and Average Current Comparison for the 3 Cases in Section V-B

The transmission window for 64 bytes (51-byte payload + 13-byte header) is 128 ms. The corresponding current consumption profile will be as shown in Fig. 5(b). Longer 'Active' mode causes successive TX windows to be separated by a large time period. Therefore, a smaller average current for both TX and RX (Table I – Case 2).

In Fig. 6(b) we see that the active region (data capture + processing) contributes almost 93% to the average current. Comparing it with the previous case the energy expenditure comes out to be 5.1 mJ per classification (this includes the energy required for TX and RX), leading to an almost 3 times increase in battery life. For a battery of 1000 mAh capacity this will fetch us a battery life of ~39 days (Fig. 7). We do this for the convenience of experimenting with different values of accelerometer frequency, microcontroller clock frequency and classification frequency.

Case 2 takes 174 seconds to perform 136 classifications. This is the case for which we conduct field trials. We never let the microprocessor go into standby mode. Fig. 5(b) shows that the current floor is always at 1 mA. This results in a high active current consumption even when the microcontroller is not doing data acquisition, processing or radio tasks.

We achieve an average current of 1.1 mA. It is lower than [14], [32] and [33] which report average running currents of 58.8 mA, 11.5 mA and 52 mA respectively. Apart from achieving a lower average current our approach lets us transmit over long distance while these works just support short range wireless protocols.

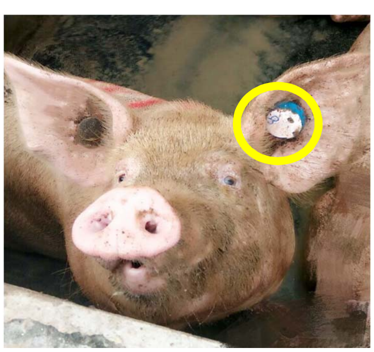

Fig. 8. Device attached to pig's ear (Circled)

3) Case 3

This case is part of future exploration as described in Section VII. With an average current of 127 µA (as tabulated in Table I), it can potentially achieve 8.5X longer battery life (Fig. 7) compared to Case 2.

VI. Case Study: Field Trials in China For activity Detection of Pigs

The custom PCB was enclosed in an injection moulded casing. The waterproof casing protects the circuitry from damage by water or by other pigs. Fig. 8 shows the device in operation attached to a pig's ear.

We considered 2 classes (High Activity/Low Activity). With accelerometer sampling frequency of 50 Hz, we define a window of 64 accelerometer samples (which corresponds to 1.28 s) as one activity. We deployed devices on 2 pigs and collected raw features for 3985 activity windows and used a camera to label these two classes. We divided the sample set as follows: 630 (training data), 2725 (test data) activity windows. The accuracy of offline training and testing obtained by our algorithm was 91.4% and 96.2% respectively. To show online testing and generalization of model on different pigs we again installed devices on 2 different pigs on the second day. This time we configured devices to accumulate 136 activity class labels and transmit once every 176 seconds. We collected 3835 samples of such activity on second day and classification labels of online classification matched with video labels for 95.5% of the samples. A lot of errors result from ear flapping which is a very common phenomenon.

To demonstrate our device's flexibility, we also performed activity classification on humans for 5 activities (sitting, standing, walking, upstairs and downstairs). With 465 training data and 279 testing data we achieved training and testing accuracy of 90% and 91% respectively with an expected battery life of 39 days. More data collection is needed for accurate performance. The intent was to demonstrate the flexibility of the system to adapt to different applications with different features for the machine learning model and different number of classes.

VII. Future Work

The wakeup time for the microcontroller [37] is <50 µs. This is much smaller than the data capture time which is of the order of milliseconds. Huge power saving can be achieved by putting MCU in low power 'stop mode' when no capturing or processing is going on. This case is illustrated in Fig. 5(c). If we optimize the current for time duration for which MCU is idle, we can get an average current of only 127 µA which would let us extend the battery life to 331 days (Fig. 7).

This is the ideal case and will be part of our future work. With the final LoRa parameters and the embedded machine learning model, the device can operate in the Case 3. From Table I we can see that, for this case an energy expense of 0.597 mJ per classification can be achieved. In comparison, [3] reported an energy per classification of 138.24 mJ for their low power bracelets.

While our current implementation (Case 1 and Case 2) can potentially benefit from traditional compression techniques, for our future direction we see kNN outperforming these techniques in terms of processing time allowing MCU to be in 'stop mode' for longer time. We would need further experimentation to benchmark such savings in processing time.

VIII. Conclusion

We designed an activity classification IoT system which benefits from the use of LoRa and embedded machine learning to save on its energy requirements. The use of embedded machine learning, with parameters mentioned in Section V-A, results in 512 times compression in data. Our choice of combining activity data before transmission and integrating LoRa into our system results in 3 times the saving in energy expenditure resulting in a battery life of 39 days. We achieve a very low energy expenditure of 5.1 mJ per classification. We propose an optimization methodology to achieve further savings in power to achieve a battery life of 331 days.

Acknowledgements

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References

[1] "ERICSSON MOBILITY REPORT on the pulse of the networked society", Nov. 2015. Web. 08 Aug. 2017.
[2] Floarea, Aurel-Dorian, and Valentin Sgârciu. "Smart refrigerator: A next generation refrigerator connected to the IoT." Electronics, Computers and Artificial Intelligence (ECAI), 2016 8th International Conference on. IEEE, 2016.
[3] Magno, Michele, et al. "DeepEmote: Towards multi-layer neural networks in a low power wearable multi-sensors bracelet." Advances in Sensors and Interfaces (IWASI), 2017 7th IEEE International Workshop on. IEEE, 2017.
[4] Haghi, Mostafa, Kerstin Thurow, and Regina Stoll. "Wearable Devices in Medical Internet of Things: Scientific Research and Commercially Available Devices." Healthcare informatics research 23.1 (2017): 4-15.
[5] Thomas, Darshana, et al. "Optimizing Power Consumption of Wi-Fi for IoT Devices: An MSP430 processor and an ESP-03 chip provide a power-efficient solution." IEEE Consumer Electronics Magazine 5.4 (2016): 92-100.
[6] Ray, Partha Pratim. "A survey of IOT cloud platforms." Future Computing and Informatics Journal 1.1-2 (2016): 35-46.
[7] Dawy, Zaher, et al. "Toward massive machine type cellular communications." IEEE Wireless Communications 24.1 (2017): 120-128.
[8] Greenberg, Albert, et al. "The cost of a cloud: research problems in data center networks." ACM SIGCOMM computer communication review 39.1 (2008): 68-73.
[9] Ravi, Prashant, Uma Syam, and Nachiket Kapre. "Preventive Detection of Mosquito Populations using Embedded Machine learning on Low Power IoT Platforms." Proceedings of the 7th Annual Symposium on Computing for Development. ACM, 2016.
[10] Lee, Jongmin, et al. "Integrating machine learning in embedded sensor systems for Internet-of-Things applications." Signal Processing and Information Technology (ISSPIT), 2016 IEEE International Symposium on. IEEE, 2016.
[11] Rizzi, Mattia, et al. "Using LoRa for industrial wireless networks." Factory Communication Systems (WFCS), 2017 IEEE 13th International Workshop on. IEEE, 2017.
[12] Augustin, Aloÿs, et al. "A study of LoRa: Long range & low power networks for the internet of things." Sensors 16.9 (2016): 1466.
[13] Park, Taehyeun, Nof Abuzainab, and Walid Saad. "Learning how to communicate in the Internet of Things: Finite resources and heterogeneity." IEEE Access 4 (2016): 7063-7073.
[14] Nachman, Lama, et al. "The Intel/sup/spl reg//mote platform: a Bluetooth-based sensor network for industrial monitoring." Information Processing in Sensor Networks, 2005. IPSN 2005. Fourth International Symposium on. IEEE, 2005.
[15] Nachman, Lama, et al. "Imote2: Serious computation at the edge." Wireless Communications and Mobile Computing Conference, 2008. IWCMC'08. International. IEEE, 2008.
[16] Adler, Robert P., et al. "Edge processing and enterprise integration: Closing the gap on deployable industrial sensor networks." Sensor, Mesh and Ad Hoc Communications and Networks, 2007. SECON'07. 4th Annual IEEE Communications Society Conference on. IEEE, 2007.
[17] Chang, Hyunseok, et al. "Bringing the cloud to the edge." Computer Communications Workshops (INFOCOM WKSHPS), 2014 IEEE Conference on. IEEE, 2014.
[18] Soto, José Angel Carvajal, et al. "CEML: Mixing and moving complex event processing and machine learning to the edge of the network for IoT applications." Proceedings of the 6th International Conference on the Internet of Things. ACM, 2016.
[19] Tei, Ritsu, Hiroyuki Yamazawa, and Takao Shimizu. "BLE power consumption estimation and its applications to smart manufacturing." Society of Instrument and Control Engineers of Japan (SICE), 2015 54th Annual Conference of the. IEEE, 2015.
[20] Dementyev, Artem, et al. "Power consumption analysis of Bluetooth Low Energy, ZigBee and ANT sensor nodes in a cyclic sleep scenario." Wireless Symposium (IWS), 2013 IEEE International. IEEE, 2013.
[21] So, Jaeyoung, et al. "LoRaCloud: LoRa platform on OpenStack." NetSoft Conference and Workshops (NetSoft), 2016 IEEE. IEEE, 2016.
[22] Sinha, Rashmi Sharan, Yiqiao Wei, and Seung-Hoon Hwang. "A survey on LPWA technology: LoRa and NB-IoT." ICT Express (2017).
[23] Ayele, Eyuel D., et al. "Performance analysis of LoRa radio for an indoor IoT applications." Internet of Things for the Global Community (IoTGC), 2017 International Conference on. IEEE, 2017.
[24] Guibene, Wael, et al. "Evaluation of LPWAN Technologies for Smart Cities: River Monitoring Use-Case." Wireless Communications and Networking Conference Workshops (WCNCW), 2017 IEEE. IEEE, 2017.
[25] Kim, Dong Hyun, et al. "Design and implementation of object tracking system based on LoRa." Information Networking (ICOIN), 2017 International Conference on. IEEE, 2017.
[26] Pham, Congduc, et al. "Low-cost antenna technology for LPWAN IoT in rural applications." Advances in Sensors and Interfaces (IWASI), 2017 7th IEEE International Workshop on. IEEE, 2017.
[27] Li, Lingling, Jiuchun Ren, and Qian Zhu. "On the application of LoRa LPWAN technology in Sailing Monitoring System." Wireless On-demand Network Systems and Services (WONS), 2017 13th Annual Conference on. IEEE, 2017.
[28] Rahman, Arrief, and Muhammad Suryanegara. "The development of IoT LoRa: A performance evaluation on LoS and Non-LoS environment at 915 MHz ISM frequency." Signals and Systems (ICSigSys), 2017 International Conference on. IEEE, 2017.
[29] Petäjäjärvi, Juha, et al. "Evaluation of LoRa LPWAN technology for indoor remote health and wellbeing monitoring." International Journal of Wireless Information Networks 24.2 (2017): 153-165.
[30] Petäjäjärvi, Juha, et al. "Performance of a low-power wide-area network based on LoRa technology: Doppler robustness, scalability, and coverage." International Journal of Distributed Sensor Networks 13.3 (2017): 1550147717699412.
[31] Escalante, Hugo Jair, et al. "Sow-activity classification from acceleration patterns: a machine learning approach." Computers and electronics in agriculture 93 (2013): 17-26.
[32] Marchioro, Gilberto Fernandes, et al. "Sows' activity classification device using acceleration data–a resource constrained approach." Computers and electronics in agriculture 77.1 (2011): 110-117.
[33] Leech, Charles, et al. "Real-time room occupancy estimation with Bayesian machine learning using a single PIR sensor and microcontroller." Sensors Applications Symposium (SAS), 2017 IEEE. IEEE, 2017.
[34] "LoRaWan Specifications v1.0.2", Oct. 2015. Web. 15 Feb. 2017.
[35] "LoRaWan Regional Parameters v1.0.2 Rev B", Oct. 2015. Web. 20 Feb. 2017.
[36] Samie, Farzad, et al. "Computation offloading and resource allocation for low-power IoT edge devices." Internet of Things (WF-IoT), 2016 IEEE 3rd World Forum on. IEEE, 2016.
[37] "STM32L073xxx Datasheet, Mar. 2016. Web. 01 Apr. 2017
[38] "SX1278 Datasheet", Rev. 4 – Mar. 2015. Web. 01 Apr. 2017