Real-Time Encoding/Decoding for Pairwise Communication Over an Unreliable Sensor Network

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Abstract: The length of time that a wireless sensor can be deployed is limited by its internal power supply. To increase the deployment lifetime of these sensors we must find ways to conserve power. In this paper, we propose an algorithm that reduces the amount of energy the transceiver consumes by compressing the bytes that are sent and received over the network. The algorithm compresses a data stream by exploiting its temporal locality and is designed to function efficiently on an unreliable network in real-time. A stream is compressed by using fewer bits to represent elements that frequently recur. We evaluate the proposed compression algorithm using a collection of independently collected traces from the crawdad database. We calculated the compression ratio for each trace and found that we were able to reduce the number of bytes transmitted by an average of 60%, resulting in a 30% increase in energy savings.

1 INTRODUCTION

Wireless sensors have been used in a variety of data collection and monitoring applications. These sensors are often deployed in locations where they do not have access to the energy grid and often rely on their internal energy supply. These locations vary from battlefields (Keally et al., 2010) and remote geological locations (Kenney et al., 2009) to deployment within the human body (Gao et al., 2005). In many cases, replacing the batteries in these sensory devices is inconvenient and costly. Addressing the problem of energy consumption in wireless sensor nodes will make the application of sensor nodes more practical.

Real-time compression algorithms have been proposed as a method for improving the energy efficiency of wireless sensors. A real-time compression algorithm reduces the amount of energy the transceiver consumes by reducing the number of bytes that are sent over the network.

Though numerous compression algorithms have been proposed, most of them are not suitable for real-time use and do not function efficiently over an unreliable network. The S-LZW (Sadler and Martonosi, 2006) and LEC (Marcelloni and Vecchio, 2008) compression algorithms are currently the state of the art real-time compression algorithms. Both algorithms are dictionary compression algorithms, which compress data by storing the compressed values and uncompressed values as key value pairs in a dictionary. The S-LZW algorithm tailors the original LZW algorithm (Nelson, 1989) to real-time embedded systems. In particular, the S-LZW algorithm trades the compression ratio of the LZW algorithm for a more efficient use of memory and the ability to tolerate packet losses. The S-LZW algorithm uses the LZW algorithm to compress the data stream in blocks. This restricts the size of the dictionary and limits packet losses to only corrupting sections of the stream. The LEC algorithm further improves on the compression ratio of the S-LZW algorithm. Unlike the state of the art algorithms, the algorithm that we propose in this paper performs efficiently over an unreliable network without delaying the stream.

The intuition behind the proposed algorithm is that the sender and receiver will automatically agree upon a set of codes that they will use to communicate. Instead of a lengthy message, the sender will transmit a shorter code that conveys the same meaning. For example, instead of transmitting the 8-bit value 00010100 for the integer 20, the sender instead sends a 2-bit value 01. The receiver then interprets the value 01 as 00010100. Communicating using a set of codes reduces the amount of energy the sensor consumes by

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reducing the number of bytes a node's transceiver has to send and receive.

We evaluate the proposed algorithm by using it to compress traces from Columbia University's EnHANTS dataset (Gorlatova et al., 2011a). The EnHANTS dataset contains irradiance (light) readings collected using TAOS TSL230rd photometric sensors. The photometric sensors were placed in different locations and readings were collected at 30 second intervals for 392 days. We compress the traces using both the proposed algorithm and the LZW algorithm. We compare the performance of the algorithms using four metrics: compression ratio, energy efficiency, memory usage, and the delay the algorithm induces on each packet. We evaluate the energy efficiency of the algorithms using the energy model for the cc2420 transceiver proposed by D Schmidt et.al (Schmidt et al., 2007).

The proposed algorithm improves on the state of the art algorithms by efficiently tolerating packet losses and reducing the delay induced on the data stream. This paper makes three contributions:

- Presents a distributed real-time compression algorithm that compresses a data stream by exploiting its temporal locality.
- Extends the algorithm to ensure that it operates on an unreliable network.
- Evaluates the compression performance and energy efficiency of the algorithm using traces collected by independent researchers.

The remainder of the paper is structured as follows: Section 2 presents the compression and decompression algorithm. Section 3 discusses the algorithm and proves its correctness. Section 4 evaluates the algorithm. Section 5 surveys the related work. Section 6 concludes the paper.

2 THE TEMPORAL COMPRESSION ALGORITHM (TCA)

Designing a real-time lossless compression algorithm presents three unique challenges. The first challenge is designing an algorithm that is able to compress data without having access to the entire data stream.

The second challenge is ensuring that the algorithm works on an unreliable network. This means that the algorithm should still be able to decompress subsequent elements if an element in the series is lost.

The third challenge is maintaining the consistency of the distributed encoding table on the sender and receiver. An encoding table is the data structure that is used to compress and decompress the stream. In a non real-time application the encoding table is constructed and sent along with the compressed data so that the compressed data can be decompressed later. However, in a real-time scenario it is not feasible to wait to send a decompression table since the receiver must decompress the values in real-time. This means that both the sender and receiver must either agree on the decoding table beforehand or independently generate the same decoding table in real-time.

Encoding tables provide a mapping from the original bytes to their compressed representations. For example, an encoding table would map the original bits 1111 to the encoding 01. Table 1 shows an example of an encoding table with 3 entries. An encoding table

Table 1: Example of an encoding table.

00	1001
01	1111
10	1000

can also be used to map a series of uncompressed values to a series of compressed values. For example the values $\{1111, 1001, 1000, 1111\}$ are mapped to the values $\{01, 00, 10, 01\}$. The same encoding table can also be used to decompress a series of values since it is a one-to-one mapping. For example, the series $\{01, 00, 10, 01\}$ can be decompressed using the same encoding table, thus resulting in the reverse mapping: $\{01, 00, 10, 01\} \rightarrow \{1111, 1001, 1000, 1111\}$.

Formally, we can think of an encoding table as a one-to-one function f that maps the original value v to its compressed form c. Written more briefly, $f : v \mapsto c$. Values are encoded by using the function f to find the corresponding encoding.

Values are decoded using the inverse of f. The inverse function f^{-1} maps the compressed value c to its original value v. The decoding function can be written more briefly as: $f^{-1} : c \mapsto v$.

Encoding tables are usually implemented using associative arrays or hashmaps. The keys of the hashmap represent the compressed values and the entries represent the original values. We can think of each entry in the hashmap as an evaluation of the f^{-1} for a specific compressed value v.

Encoding tables are normally used by a class of compression algorithms called dictionary encoders. Dictionary encoding algorithms compress data by reading all the data and constructing an encoding table which is then packaged along with the compressed data, so that it can be decompressed later.

Creating an encoding table for all the data is not feasible in a real-time scenario, since the algorithm will not have access to all the data beforehand. This means that the algorithm on the sender must dynamically create the encoding table and communicate it without affecting the real-time constraints of the application.

Algorithms 1 and 2 show how the sender and receiver dynamically create the encoding table without any communication overhead. The algorithms dynamically create an encoding table by caching the last *N* values. A value's encoding corresponds to its index in the encoding table. If a value reoccurs, the algorithm compresses it by reporting its index in the encoding table. If a value is added to an encoding table for the first time the algorithm reports the value instead of the index. Reporting the value instead of the index allows the receiver to update its encoding table so that it is consistent with the sender.

During the remainder of this section, we discuss a detailed example. We use this example to explain how algorithms I and II are used to establish the distributed encoding tables dynamically.

Algorithm 1: Algorithm For Compressing Packets.

Input: Packet To Encode (PTE) , *N*-bitCounter, Encoding Table
Output: Encoded Packet (EP)
if *PTE is an entry in the Encoding Table* **then**
  EP←Index of the [Entry] **return** EP
else
  Increment *N*-bitCounter
  Encoding← *N*-bitCounter Add Entry [PTE] at Index [Encoding] **return** PTE
end

Algorithm 2: Algorithm For Decompressing Packets.

Input: Packet To Decode (PTD) , *N*-bitCounter, Encoding Table
Output: Decoded Packet (DP)
if *length(PTD)*$\leq \log_2(N)$ **then**
  DP←Entry in Encoding Table at Index PTD **return** DP
else
  Increment *N*-bitCounter
  Encoding← *N*-bitCounter Add Entry [PTD] at Index [Encoding] **return** PTD
end

Figure 1 shows an example of how the datastream $\{1111, 1010, 1111, 0000\}$ is compressed and decompressed in real-time. As the first value 1111 arrives, it is inserted at the first index in the encoding table. In this example, we consider an encoding table that holds a maximum of two encoding pairs. Each value is encoded using the index of the value in the table.

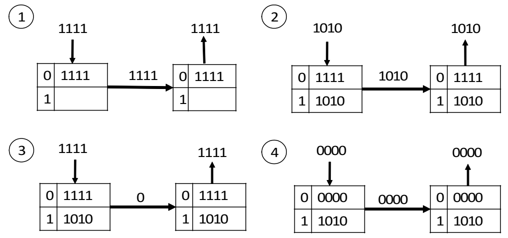


Figure 1: The diagram above shows an example of how the algorithm compresses and decompresses a stream of information in real-time.

Since the value 1111 is the first in the series it is inserted at the first index in the encoding table: 0. This is because there are two positions in the table and each position can be addressed using a single bit. The value 0 corresponds to the first position while value 1 corresponds to the second position in the table. We use the 1-bit counter to track the next available position in the decoding table. In this example the encoding table is restricted to a maximum of two encoding pairs so we use a 1-bit counter to represent the index values $\{0, 1\}$.

Once the value 1111 is placed into position 0 the following encoding pair $\{1111\} \rightarrow \{0\}$ is created. The sender then sends the value 1111 to the receiver, so that the receiver can establish the same encoding pair for the value 1111. Upon receipt of the update value 1111 the receiver inserts the value at the first index of its decoding table, thus creating the following encoding pair $\{0\} \rightarrow \{1111\}$. Now that the decoding table on the receiver has been synced with the encoding table on the sender, the next time the sender encounters the value 1111 it can simply send the compressed value 0 and the receiver will be able to decompress the value and interpret it as the value 1111.

Both the sender and receiver maintain a 1-bit counter. Upon encountering a new value both the sender and receiver increment the 1-bit counter. If both counters on the sender and receiver start with the same index value, every entry will be assigned the same encoding value on the sender and receiver since both counters are incremented in sync.

The compression and decompression algorithms follow the same procedure for the next value 1010. Since the value is not contained in the encoding table it will be added to the encoding table. So both algorithms increment their 1-bit counters and insert the value into the encoding table at position 1.

However, the third packet is treated differently because the packet is already contained in the encoding table of the sender. This implies that the encoding scheme has already been established for this packet. Therefore, the sender sends the encoded value 0 instead of the value of 1111. The Receiver checks the length of the value and determines that it corresponds to an encoding value. It then looks up in the encoding table and returns the value at position 0 which is 1111.

Limiting the size of the encoding table helps decrease the lookup time so that the compression and decompression processes meet the real-time constraints of the application. An N-bit counter only allows for 2^N possible encoding keys. The 1-bit counter in this example only allows for two encoding keys.

When the fourth value (0000) arrives, all the entries in the encoding table have been filled. Therefore one of the entries must be overridden, since the encoding table can only hold two unique entries. The first value is overwritten, since the N-bit counter is cyclic, so the fourth packet is placed at the first index. This does not affect the consistency of the encoding tables, since the counters are cyclic, both the sender and receiver override the same value in the encoding table.

3 DISCUSSION OF TEMPORAL COMPRESSION ALGORITHM

3.1 Proof of Correctness

Let S be a stream of packets $\{p_1, p_2 .... p_n\}$. Let $f_x(p_i)$ denote the compression function implemented using a hashmap of size x. Recall that this hashmap represents the encoding table that was described earlier in this section. We formally define the compression function below in equation 1.

$$f_x(p_i) = \begin{cases} p_i & \text{if} \quad H_x(p_i) = \emptyset \\ H_x(p_i) & \quad \text{otherwise} \end{cases} \tag{1}$$

The function $H_x(p_i)$ denotes the hash function that is applied to the packets. We denote the length of a packet as $|p_i|$. We detect compressed packets by examining their length $|p_i| \leq \log_2(x)$. The decompression function is formally denoted below.

$$d_x(p_i) = \begin{cases} p_i & \text{if} \quad |p_i| > \log_2(x) \\ H_x^{-1}(p_i) & \text{if} \quad |p_i| \leq \log_2(x) \end{cases} \tag{2}$$

Theorem 1 (Dictionary Consistency)**.** *The dictionary on the sender s remains consistent with the dictionary on the receiver r for any arbitrary data stream of ordered packets.*

Proof. To prove the correctness of the algorithm we must show that the following invariant holds.

Invariant:

$$d_x(f_x(p_i)) = p_i \tag{3}$$

Maintenance of Invariant: We must prove that the invariant holds in two cases. The first case is when the packet is not in the hash table, while the second case is when the packet is in the hash table.

In the first case the packet has not been compressed and $|p_i| \geq \log_2(x)$ and therefore the decompression function correctly returns the value. The invariant holds in this first case.

In the second case, equation 4 must be true for the invariant to hold.

$$H_x^{-1}(H_x(p_i)) = p_i \tag{4}$$

Equation 4 is true by construction, since every key value pair that is inserted into the hash table $H_x(p_i)$ is also inserted as an inverse key value pair in the $H_x^{-1}(p_i)$ in which the value is treated as the key and the key is treated as the value.

Termination: The algorithm will terminate because the data stream is of finite length and the algorithm only operates on each packet once. The algorithm has a time complexity that is linear with the number of packets.

□

3.2 Dealing with Packet Losses

In this section we demonstrate how the proposed algorithm deals with packet losses. To aid our explanation, we introduce three categories of packets: update packets, compressed packets and locking/unlocking packets. Update packets cause new key value pairs to be inserted into the encoding table. compressed packets contain the encoded values. Locking packets are used to lock the encoding table, while unlocking packets are used to unlock the encoding table. Locking the encoding table prevents new packets from being added to the encoding table.

The loss of a compressed packet is naturally tolerated by the algorithm, since compressed packets do not affect the consistency of the encoding table. However, if an update packet is lost the encoding table on the sender will become inconsistent with the encoding table on the receiver. There are two methods for ensuring the consistency of the encoding tables. The first method uses acknowledgments to guarantee the delivery of update packets, while the second method prevents a lost update packet from updating the encoding tables by locking the encoding tables. Each method has trade-offs. The first method is suited for periods of high temporal locality, while the second method is suited for periods of low temporal locality.

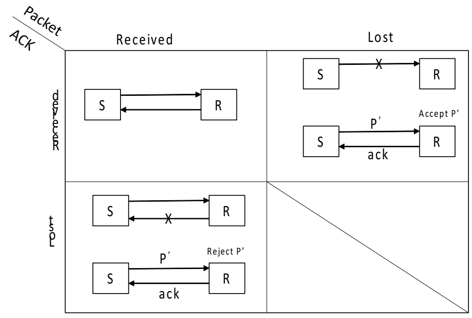


Figure 2: A Karnaugh map showing a visual proof that the algorithm guarantees delivery of all update and control packets under different loss conditions. P' represents the duplicate packet while X represents a lost packet.

The proposed algorithm accommodates data streams with sections of both high and low temporal locality by using both methods. The first method is discussed in subsection 3.3 And the second method is discussed in subsection 3.4

3.3 Using Acknowledgments for Update Packets

The sender and receiver use acknowledgments to guarantee the delivery of update packets, locking packets, and unlocking packets. The sender starts a timer and waits for an acknowledgement from the receiver. Once the sender has sent an update packet the sender does not update its encoding table or send another packet until it receives an acknowledgement from the receiver. If the sender does not receive an acknowledgement within a given time period the sender resends the packet. The receiver gets a duplicate update packet and resends and acknowledgement. By using acknowledgments both the sender and receiver guarantee the consistency of their encoding tables. To prove that this mechanism works in all scenarios we use the Karnaugh map shown in figure 2 to construct a visual proof.

The first cell in the Karnaugh map represents the condition in which both the packet and the acknowledgment are received. In this case the algorithm functions normally.

The second cell represents the condition under which the packet is lost but the acknowledgment is received. This state is not possible since the receiver will only acknowledge packets that it has received.

The third cell represents the condition under which an update packet has been received but the acknowledgment has been lost, in which case the sender retransmits the packet. When the receiver receives the re-transmitted packet it checks to see if it has already received the packet by checking the last entry in the decoding table. If the update packet is already contained in the decoding table, the receiver knows that it has already received the packet and can conclude that the acknowledgment was lost. Once the receiver has concluded that the acknowledgement has been lost it retransmits the acknowledgement to notify the sender that it has received the packet.

It may seem that this recovery strategy would fail if the stream contains two consecutive and identical update packets since this strategy would drop the second packet. However, update packets cannot be duplicated in a sequence. By definition, if the packet following an update packet is identical to the update packet it will be encoded using the update packet's index, thus making it a compressed packet. Consider the following example data stream: $\{0001, 0010, 0010\}$. The second packet 0010 is a compressed packet since the first packet would have already been stored in the update table. So, instead of sending the value 0010, the algorithm would transmit the index, which is a compressed packet.

The fourth cell represents the condition under which the update packet is lost. If an update packet is lost, the algorithm will follow the same procedure described above to ensure that the encoding tables are kept consistent. It should be noted that using acknowledgements would result in a slight delay since sender and receiver would wait until the acknowledgment is received.

The algorithm tolerates out-of-order arrivals for compressed packets but does not tolerate out-of-order arrivals for update packets. However, this is not a problem because the algorithm ensures the in-order arrival of all update packets by buffering the stream until it has received an acknowledgment.

3.4 Locking the Encoding Table

Acknowledging packets introduces additional delay, since the sender must wait for an acknowledgement before allowing the stream to progress. Such delays may outweigh the benefits of the compression algorithm. This is tolerable, if update packets are rare then acknowledgments are rarely sent. However, if update packets are common then acknowledgments have to be sent frequently. Frequent update packets imply low temporal locality and the benefits of the compression may not be worth the delay. To mitigate this we propose locking the encoding table. Locking the table stops any additional packets from being added to the encoding table; thus removing the need for acknowledgments.

To ensure that the algorithm functions efficiently we lock the table during periods of low temporal locality and unlock the table during periods of high temporal locality. We propose using the number of unique packets within a given time period as a measure of temporal locality and propose locking the table when the rate of unique packets rises above a fixed threshold and unlocking the encoding table when the rate of unique packets falls below a set threshold. This threshold is determined empirically.

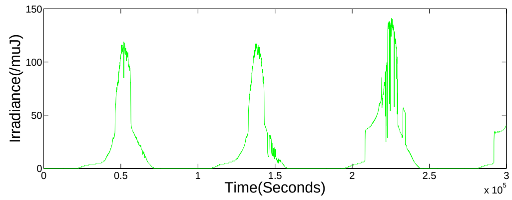
4 EVALUATION

We have evaluated the proposed Temporal Compression Algorithm using four metrics: 1) the compression ratio, 2) the energy used by the transceiver, 3) the number of bytes required for compression. We use these metrics to compare the temporal compression algorithm to the state of the art LZW algorithm. The the temporal compression algorithm reduces the amount of energy used by the transceiver by 30% when compared with the uncompressed data stream. The temporal compression algorithm does not delay any packets, while the LZW algorithm delays an average of 80% of the packets.

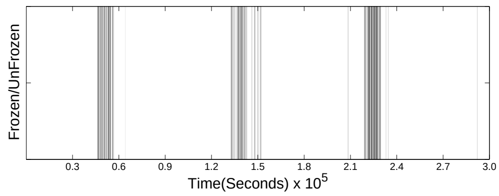
We evaluate the performance of our algorithm by examining four traces of irradiance readings obtained from Columbia University's EnHANTs dataset (Gorlatova et al., 2011b). The readings were collected at 30 second intervals using TAOS TSL230rd photometric sensors installed on LabJack U3 DAQ devices. Each trace was collected from a sensor placed in a different location. The first trace (Setup A) was collected from a sensor placed on the windowsill of a south-facing window on the 6th floor of a building. The second trace (Setup B) was collected from a sensor placed on top of a bookshelf; this sensor only received light for a short portion of the day. The third trace (Setup C) was collected using a sensor placed on the windowsill of a north-facing window in a conference room where the shades were frequently adjusted. The forth trace was collected by holding a sensor and walking around time square in New York City.

4.1 Compression Performance

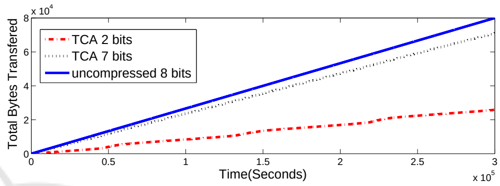
We evaluate the compression performance of an algorithm by calculating its compression ratio. The compression ratio is calculated by dividing the size of the compressed data by the size of the original data. A compression ratio of 0.5 means that the compressed data is half the size of the original data. We calculate the compression ratio of the TCA algorithm and compare it to the compression ratio of the LZW algorithm.



(a) Irradiance Readings



(b) State of Encoding Table



(c) Total Bytes Transferred

Figure 3: Figure (a) shows the irradiance reading vs time. Figure (b) is a color map. This color map shows the state of the encoding table. Dark regions represent a locked state while light regions represent an unlocked state. Figure (c) shows the total number of bytes transmitted.

Figure 3(a) shows 10,000 irradiance readings collected over a period of 83.333 hours (3.5 days). These readings were taken from the trace associated with setup A. Notice the periodicity between the low irradiance readings and high irradiance readings.

Figure 3(b) shows a colormap. The x-axis shows the time, while the color of the map represents the state of the encoding table. Dark regions indicate that the encoding table is in a locked state, while light regions indicate that the encoding table is in an unlocked state. We ran the TCA algorithm using a table size of four and a threshold of four update packets every two minutes. As expected dark regions on the map correspond to sections of low temporal locality while light regions of the map correspond to sections of high temporal locality. Therefore we conclude that using a threshold to identify sections of high and low temporal locality is an effective strategy for determining when to lock and unlock the encoding table.

Figure 3(c) shows the total number of bytes vs. time. The solid blue line represents the total number of bytes that would be transferred if the stream was uncompressed (8 bits). The dotted black line represents the total number of bytes that would be transferred if the data was compressed using the 7-

Table 2: (NC) No Compression, (TCA) Temporal Compression Algorithm, (LZW) Lempel Ziv Welch Algorithm.

Trace	Algorithm	Compression Ratio	Memory (bytes)	Energy Range (J)
Setup A EnHANTs	TCA	0.3233	4	0.0144 → 0.0246
	LZW	0.1605	930	0.0030 → 0.0055
Setup B EnHANTs	TCA	0.2626	4	0.0139 → 0.0236
	LZW	0.0546	401	0.0009 → 0.0018
Setup C EnHANTs	TCA	0.2978	4	0.0142 → 0.0242
	LZW	0.0791	523	0.0015 → 0.0026
Mobile Trace EnHANTs	TCA	0.7261	4	0.0064 → 0.0113
	LZW	0.5121	1050	0.0034 → 0.0062

bit encoding temporal compression algorithm. The dashed red line represents the total number of bytes that would be transferred if the data was compressed using the 2-bit encoding temporal compression algorithm.

Figure 3(c) shows how increasing the number of encoding bits affects the compression ratio. Using a 2-bit encoding scheme achieves a better compression ratio than using a 7-bit encoding scheme, because the 2-bit encoding scheme allows for smaller encoded packets, which makes up for its inability to capture the diversity in the stream since it only encodes 4 values (2^2). Though a 7-bit encoding scheme encodes up to 128 values, the compressed packets are 7-bits, 5 bits larger than the encoded packets used by the 2-bit encoding scheme. Since the sections of the data stream that exhibit high temporal locality contain less than 4 unique values; the 2-bit encoding scheme is better suited for this trace.

We found that the temporal compression algorithm is able to achieve an average compression ratio of 0.398. This means that the temporal compression algorithm allows the transceiver to transmit an average of 60% fewer bytes than the uncompressed stream.

4.2 Energy Efficiency

The energy model for the CC2420 transceiver proposed in (Schmidt et al., 2007) is used to evaluate the energy efficiency of the algorithms. The CC2420 transceiver is commonly found in sensor nodes like micaz (Polastre et al., 2005).

It is not energy efficient to send a payload that is only 8 bits long, since 18 bytes of additional information must be transmitted along with it. Several sensing applications solve this problem by packaging multiple packets into the 28 byte payload. The receiver recovers the packets by parsing the payload. When simulating the energy consumption of the LZW and temporal compression algorithm we place multiple packets in the payload of each data frame. Each data frame is packed with 24 packets. Each packet may be an update packet or a sparse packet. A 24 bit boolean array is used to indicate the index of sparse packets and update packets. A boolean value of 1 means that the packet is an update packet while a boolean value of 0 means that it is a sparse packet. The boolean array is stored at the beginning of the frame's payload. The receiver uses the boolean array to parse the frame's payload.

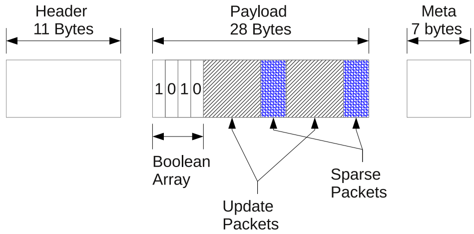


Figure 4: 802.15.4 frame layout.

Figure 4 shows an example of a data frame. The payload in this example is approximately 4 bytes long and contains 2 update packets and 2 sparse packets. Typical payloads will contain 24 packets, however for the purpose of this example we only show 4 packets. Since the payload only contains 4 packets, 4 bits of payload are reserved for the boolean array $\{1,0,1,0\}$. The receiver uses this boolean array to parse the payload. A boolean value of 1 means that the receiver should read the next 8 bits as the value for the update packet, while a value of 0 means that the receiver should read the next 2 bits as the value for the sparse packet. In our experiments the payload was filled with 24 packets. This results in a boolean array that is only 3 bytes long.

5 RELATED WORK

Dictionary coding algorithms have been proposed as an alternative to tree based encoding algorithms. Dictionary coding algorithms encode values by storing the compressed value and the original value as key value pairs in a dictionary. This results in fast encoding and decoding times but does not address the space constraints of embedded devices, as the dictionaries can become very large.

The LZ77 algorithm encodes data using a dictionary and sliding window (Ziv and Lempel, 1977) . The algorithm works by sliding an expanding window across the bytes stream. If the bytes in the window are in the dictionary the algorithm reports the index of the bytes. If the bytes in the window are not in the dictionary the algorithm adds the bytes to the dictionary. However, the LZ77 algorithm does not meet real-time constraints as the entire data stream is needed in advance to construct the dictionary.

The LZW algorithm (Nelson, 1989) attempts to address some of the real-time constraints of the LZ77 algorithm. The LZW algorithm is also a dictionary coding algorithm and is a modification of LZ78 (Ziv and Lempel, 1978), which is based on the LZ77 compression algorithm. The LZW algorithm starts by initializing the dictionaries on the sender and receiver with 256 entries. As the sender gets values it encodes the values using the dictionary. If the sender gets a value that is not in the dictionary it adds the value to the dictionary and sends the value to the receiver so that it can also add the value to its dictionary. This is how the algorithm ensures that both the dictionaries on the sender and the receiver are consistent while still meeting the real-time constraints. However, this algorithm fails if a single packet is lost. The loss of a single packet corrupts the dictionaries. The algorithm does not impose a size constraint on the dictionaries. This means that the dictionaries can grow to be very large. It is difficult to store large dictionaries on sensor devices with limited memory.

The S-LZW (Sadler and Martonosi, 2006) algorithm was introduced to address the memory constraints and packet loss constraints of the LZW algorithm. The S-LZW algorithm restricts the dictionary to 512 entries and divides the data stream into independent blocks. A new dictionary is created for each block. If the dictionary is filled, it is frozen, and no new entries are added.

6 CONCLUSION

In this paper we present a real-time compression and decompression algorithm for unreliable networks. The algorithm compresses a data stream by exploiting the stream's temporal locality. Fewer bits are used to represent elements that frequently recur in a temporal sequence. The sender and receiver automatically agree upon the bits that will be used to encode the elements. These bits are then stored in encoding tables which are used to compress and decompress the data in real-time.

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