Wireless Sensor Networks: A Monitoring Tool for Improving Remaining Lifetime Estimation?

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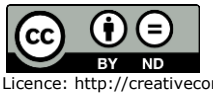
Abstract. In the past decade, wireless sensor networks (WSNs) have emerged as an innovative structural monitoring technology. Their advantages such as rapid deployment, ease of scalability, and self-configuration allow to reduce the costs, to increase the flexibility, and to simplify the operability of monitoring. However, these advantages are weakened by the power limitations that impose low power hardware with limited resources and carefully chosen data acquisition, data processing and data communication policies. Based on three real-life deployments, this paper shows that despite the scarce resources and the still existing deficiencies current wireless sensor networks allow users to reliably perform demanding and practically relevant monitoring tasks.

1 Introduction

In the last years, wireless sensor networks (WSNs) have emerged as a promising technology in the field of structural monitoring. A wireless sensor network is a computer network consisting of many small, intercommunicating computers equipped with one or several sensors. Each small computer represents a node of the network and is commonly called sensor node. The communication within the network is established using radio frequency transmission. The typical hardware components of a sensor node are sensors, a signal conditioning unit, an analog to digital conversion (ADC) module, a central processing unit (CPU) with random access memory (RAM), a radio transceiver and the power supply. Various wireless sensor networks platforms are commercially available today, which offer the basic functionality together with specific sensing capabilities ([1]).

Contrary to conventional monitoring systems, which usually support a centralized system configuration and data acquisition, a WSN is a distributed system. Each sensor node executes software for performing many tasks: scheduling of the measurements, signal conditioning and data acquisition for different sensors, temporary storage of the acquired data, data processing, self monitoring (e.g. supply voltage, communication link quality), time synchronization of the network, configuration of the data acquisition and processing (e.g. changing the sampling rate, reprogramming of data processing algorithms), reception and forwarding of data packets etc. ([2]).

The main advantages of wireless sensor networks are fast deployment, easy scalability, little interference and self-configuration. However, since wireless sensor nodes are battery powered, in medium and long term monitoring applications the power management influences significantly the operation of a wireless sensor network. In data



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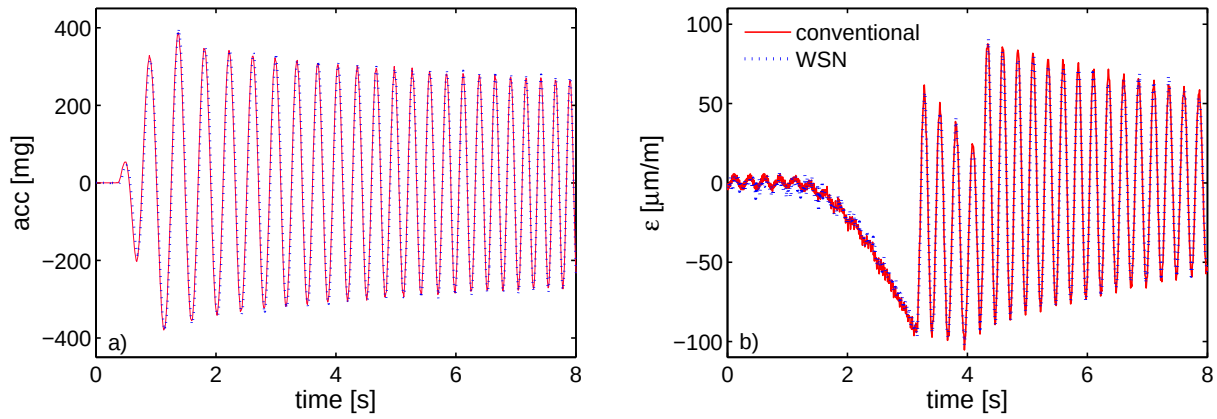

Figure 1: a) Acceleration records obtained with a sensor node and a wired data acquisition device with a conventional piezoelectric accelerometer. b) Strain records obtained with a WSN and a wired data acquisition device.

intensive applications, e.g. vibration based monitoring, the standard power saving mechanisms such as low power hardware, duty cycle operation and efficient communication policies are not sufficient for achieving a sustainable system lifetime. Since data communication is the most energy consuming task, long lifetimes can only be achieved by performing a significant reduction of data already in the nodes. This data reduction is a challenging task, since it has to be performed with very limited computational and memory resources.

The objective of the paper is to present our experience over the past years with the development and real-life deployments of WSNs for data intensive structural monitoring.

2 Data Acquisition Aspects

2.1 Sensors

Very early experimental and commercial WSN platforms already offered specific low power data acquisition boards with integrated MEMS sensors and signal conditioning circuits for sensing and acquiring temperature, humidity, light intensity, gas pressure, accelerations etc. MEMS sensors have several advantages compared to conventional sensors: They are small, generally low power (a few mW), highly integrated and, if no high end accuracy is required, inexpensive. Figure 1a displays a comparison of the performance of a 10 € MEMS accelerometer and a 500 € conventional piezoelectric accelerometer. The accelerations of the MEMS accelerometer were recorded with a sensor node equipped with a 12 bit ADC and those of the piezoelectric accelerometer with a 24bit high end data acquisition device. The agreement displayed in Figure 1a is very good. In the investigated amplitude range both accelerometers are essentially equivalent.

Nevertheless, conventional sensors can also be easily supported by WSN monitoring systems. For conventional sensors, the suitability is usually given by the power consumption and the complexity of the signal conditioning. A typical widely used conventional sensor in structural monitoring is the electrical resistance strain gage. Figure 1b displays strain records obtained with a WSN and a conventional high end data acquisition device. The quality of the WSN record is comparable to the record obtained with the conventional system. The average difference between the two records has a magnitude of a few percent. Unfortunately, because of its low resistance (typically 120 Ω), strain gages are rather power consuming (approx. 40 mW).

2.2 Analog to Digital Conversion

Today's wired data acquisition devices are typically equipped with 24 bit AD converters. In contrast, mainly for reducing the power consumption, typical WSN platforms are provided with 8 or 12 bit ADCs. This represents a quite stringent limitation that requires for each application a careful balance between resolution and amplitude range. At low amplitudes the quantization effect of the ADC limits the resolution of the data acquisition process. This effect is expressed by noise and can be observed in the first two seconds of the record of Figure 1b. Contrary, at large amplitudes, Figure 1b does not display a significant difference between the data obtained by the sensor node and the high end data acquisition device. 16 or 24 bit ADCs suitable for WSNs are commercially available and can be easily integrated. The benefit of a larger dynamic range is, however, paid by greater power consumption. Whereas the power consumption of a 12 bit ADC is typically 0.5-1 mW, a 24 bit ADC consumes typically several mW.

2.3 Data Acquisition Policies

Currently, the typical data acquisition used with WSNs is permanent, on demand and periodical data acquisition. Permanent data acquisition starts when the sensor node is switched on and stops by switching off the node. Data acquisition on demand is controlled with specific start and stop commands that are triggered by an operator or a back-end software and are sent to each node of the network with a broadcast message ([2]). Periodical data acquisition requires that each node has a remotely configurable scheduler that triggers autonomously the measurements. Since each node performs the data acquisition autonomously according to its local clock, synchronisation in time has to be enforced by a time synchronisation mechanism.

Event driven data acquisition, which is a very common data acquisition policy for wired monitoring systems, has hardly been investigated for WSNs. Because of the distributed character of a WSN, the triggering of data acquisition based on an external signal is more complex as for centralized systems. The complexity increases even more if a time synchronized data acquisition is required. The simplest solution, which mimics wired centralized systems, is to operate a node with permanent data acquisition and to check for an event using a threshold value. In case of an event the data is forwarded to the next processing step, which can be additional in-node data processing steps or just a transmission of the acquired data. In case that no event occurred the memory with old data is overwritten with new data. This simple solution, however, works only satisfactorily if the sensing and data acquisition process is low power or if the deployment period is short. Otherwise, the power supply is depleted too quickly with respect to the deployment period requiring frequent and possibly costly battery replacements to keep the WSN in operation.

3 Deployments

3.1 Monitoring of Stay Cables

A WSN for monitoring stay cable tension was deployed during 4 years on the Stork Bridge in Winterthur, Switzerland. The network consisted of 6 nodes (C1 to C6), which were mounted on 6 stay cables, a root node (C0), which was located at the northern abutment under the bridge deck, and a relay node, which was mounted beside the bridge. Figure 2a illustrates the set-up and Figure 2b displays the sensor nodes mounted on stay cables of the Stork Bridge.

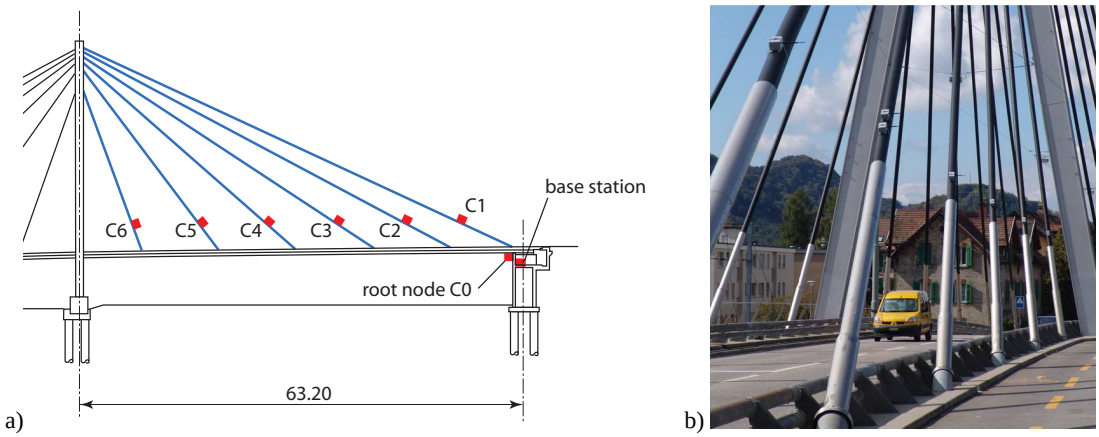

Figure 2: a) Set-up of the WSN monitoring system. b) Stay cables of the Stork Bridge with mounted sensor nodes.

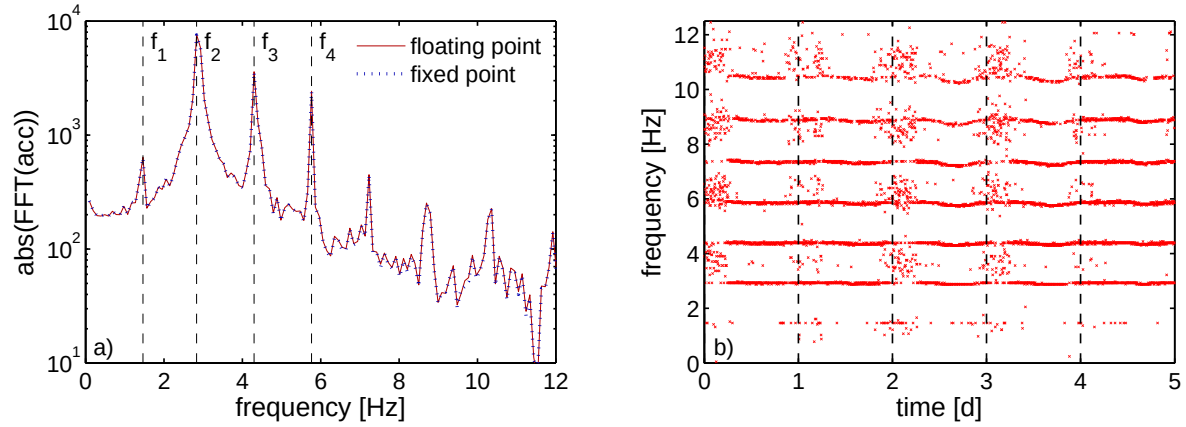

Figure 3: a) Spectra of an ambient vibration record computed with floating and fixed point operations. b) Time evolution of the monitored natural frequencies of cable C2.

Cable tension can be estimated by correlating the measured natural frequencies, which are extracted from ambient vibration records, with natural frequencies predicted with a cable model. Since the natural frequencies are the only information needed to estimate the cable tension, they are extracted by in-node data processing and transmitted to the network sink, while the raw data can be discarded. From the initial amount of data, thousands of samples, the data to be communicated is thus reduced to 8 natural frequencies.

Vibrations were measured with a MEMS capacitive accelerometer. The ambient vibrations were recorded with a sample rate of 50 Hz for 20.5 seconds (1024 samples). The power consumption of the accelerometer and signal conditioning was approximately 5 mW. In addition, temperature and humidity were measured with a single chip MEMS sensor. All data was acquired periodically with a time interval of 5 minutes.

The computation of the natural frequencies was performed in several steps. First, an FFT of the vibration recorded was carried out. The FFT was computed using fixed point operations. It is 10 times faster as a floating point FFT and, by performing a suitable scaling of the raw data, provides essentially the same accuracy (Figure 3a). The next steps consisted in computing the frequency spectrum (ℓ_2 norm) and normalizing it with an algorithm that enhances the peaks. Finally, 8 natural frequencies were computed with a peak-picking algorithm. The computation of natural frequencies took less than 1 second.

Figure 3b shows the time evolution of the natural frequencies of cable C2. 6 natural frequencies could be regularly monitored for this cable. The first natural frequency and the natural frequencies with a magnitude greater than 11 Hz were more difficult to detect since the associated vibration modes were scarcely excited by the traffic. The standard deviation

a) b)

Figure 4: a) Monitored timber footbridge. b) Sensor node mounted on the support of the handrail.

of the natural frequency estimations of cable C3 was less than 0.05 Hz and exhibited therefore approximately the same magnitude of the frequency resolution of the spectrum, which was 0.05 Hz. The 1h average of the natural frequencies (12 estimations) of the cable C3 differed from accurate reference measurements by less than 2%. Regularly, between midnight and 5 am the estimations of natural frequencies were very imprecise. This result occurred because the very sparse traffic during this time period generated very small vibration amplitudes that were of the same order of the system resolution. Figure 3b, however, demonstrates that the resolution was good enough to track the temperature induced changes of the cable forces.

3.2 Vibration Monitoring of a Footbridge

The second deployment example concerns the vibration monitoring of a footbridge. Vibration monitoring is often used for serviceability assessment. In this context, the most important information is pedestrian induced vibration amplitudes.

The structure under investigation was a three span timber bridge in Mellingen, Switzerland (Figure 4a). The deployment consisted of 4 sensor nodes (Figure 4b) and a relay node. The sensor nodes had the same hardware of the Storck Bridge: a MEMS accelerometer and a temperature/humidity sensor. All nodes recorded permanently the vibrations. Temperature and humidity were recorded periodically. In two nodes, the in-node data processing consisted in estimating natural frequencies. The same algorithm of the Stork Bridge deployment was used. The other two nodes were programmed to provide vibration amplitudes. However, since only pedestrian induced vibrations were of concern, a simple event driven mechanism was implemented. Only records with at least one amplitude value exceeding a threshold value of 0.02 ms^{-2} were processed. For these records, the envelope of the record was computed and transmitted to the base station. The envelope was defined by selecting the maximal and minimal vibration amplitudes within subsequent chunks of raw data of 50 samples each (1 second recording period). Computing the envelope took 20 ms. The data size for transmission could be reduced to 5% of the original raw data size thus providing an energy saving by a factor 20. Furthermore, processing and transmitting only data that exceeded the threshold value resulted in an additional energy saving.

The WSN monitoring system was deployed on September 7th 2011 and the deployment lasted two hours. Each sensor node was equipped with 4 batteries with a capacity of 16’500 mAh. The first replacement of batteries was done on April 11th 2012 because the supply voltage was approaching the lower bound of 2 V that was required for operating properly the temperature/humidity sensor. The battery replacement period was thus 7 months. Batteries replacement could be performed within an hour.

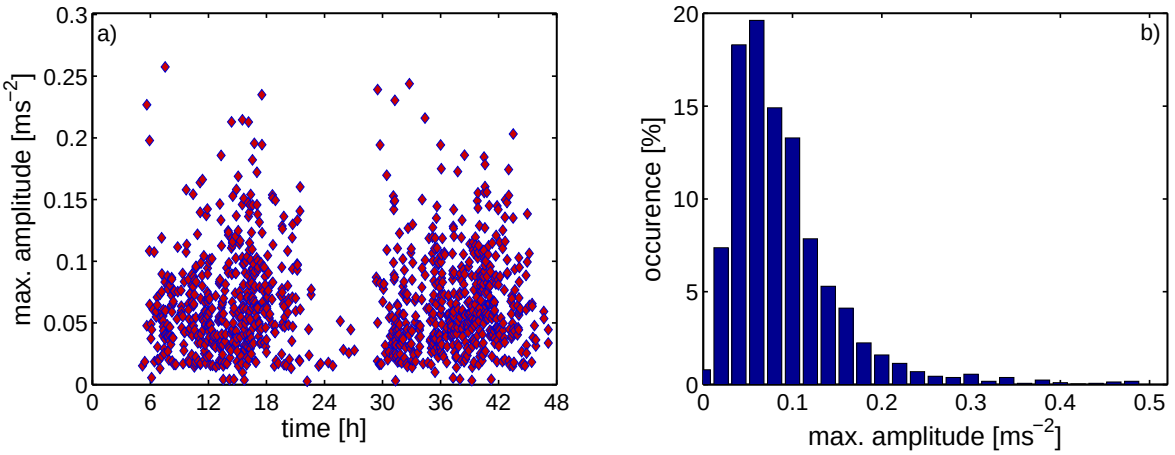

Figure 5: a) Time distribution of maximum vibration amplitude of records. b) Histogram of maximum vibration amplitudes of records.

Figure 6: a) The Keräsjokk Railway Bridge. b) Strain gages and a sensor node on a stringer.

The recorded envelopes were post-processed to extract the maximum vibration amplitude. Figure 5a displays the time distribution of these maximum vibration amplitudes during 2 days. The plot shows that the bridge is used by pedestrians from 6 am to 22 pm and that most of the maximum vibration amplitudes are smaller than 0.2 ms^{-2}. The histogram of maximum vibration amplitudes displayed in Figure 5b covering a period of 7 months confirms essentially this finding.

This type of statistical data, which is obtained by monitoring during operations, often allows to perform a more realistic vibration assessment than the traditional method that is based on specific vibration tests with a few pedestrians combined with model simulations. In addition, fast deployment and long batteries lifetime of WSNs makes monitoring based vibration assessment economically competitive.

3.3 Strain Monitoring of a Railway Bridge

In remaining lifetime estimation the knowledge about stresses under operation conditions is of outstanding importance. Information about stresses can be achieved with strain monitoring. The last deployment example addresses this issue describing the monitoring of a bridge over the Keräsjokk River on the Haparanda railway line (single track, non-electrified) in Northern Sweden. The bridge is a single span, simply supported riveted steel truss bridge with a length of 31.6 m (Figure 6a). The railway tracks lies on wooden sleepers directly on the stringers (no ballasting). The bridge was crossed one or two times per day by heavy freight trains.

The WSN deployed on the bridge consisted of 8 nodes and the root node connected to the base station. Six strain measurements were performed on a longitudinal stringer and two measurements were mounted on a floor beam. The strain was measured with soldered strain gages featuring a resistance of 120 Ω. Figure 6b shows deployed sensor nodes and strain gages mounted on the stringer. The strain gages were connected to the nodes of the

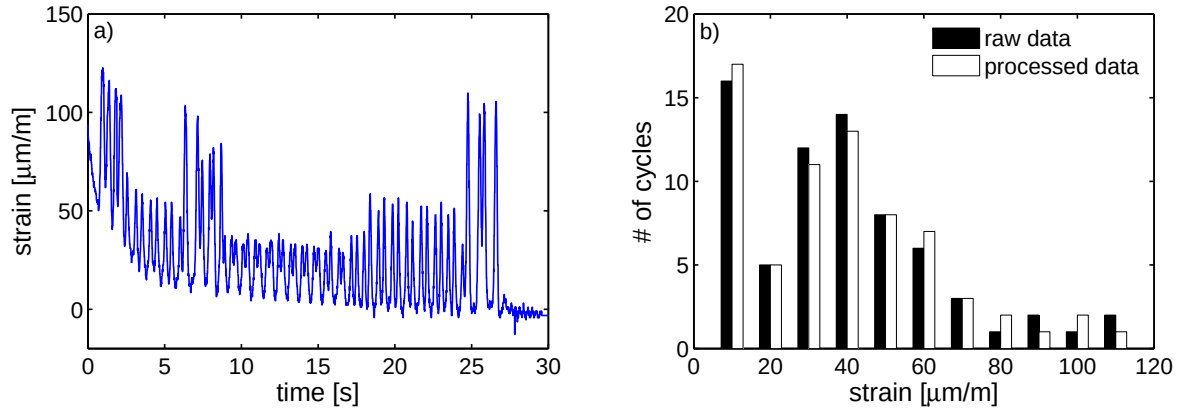

Figure 7: a) Biased strain record. b) Histogram of strain cycles.

wireless sensor network by cables, which were plugged into an external connector. The housings of the nodes were equipped with four magnetic footings, which allow a fast mounting. Since the strain gauges had been installed in advance, the installation was quite fast and took approximately 4 hours.

The data was recorded with a sampling rate of 100 Hz and the record period was 30 seconds (3000 samples). The total memory requirement of a record was of the RAM memory of the microcontroller. All the recorded data was sent to the base station. To avoid packet collision, a transmission policy was chosen that provided for each node a time slot for transmitting its data. The wireless monitoring system recorded also temperature, humidity, supply voltage and network data with a time interval of 2 minutes.

Since electrical strain gages are quite power consuming, a 120 Ω strain gage consumes approx. 40 mW, a long-term operation required the implementation of a power saving mechanism. Because of the very low traffic on the bridge, switching on the strain sensing hardware only during train crossing would allow a significant power saving. This policy, however, requires a triggering mechanism that consumes significantly less power than a strain gage. A solution was found by equipping the sensor nodes with an ultra low power (500 µW at full operation mode) MEMS acceleration sensor that was permanently running for identifying approaching trains through vibrations. The sensor had a built-in signal processing capability for analyzing the acquired accelerations. If a specified threshold vibration amplitude was exceeded, the strain sensing module (strain gage and signal conditioning) was switched on and the data acquisition was started. This wake up process lasted 100 ms. After the recording was completed the strain sensing module was switched off. Each node was triggered independently.

A typical recorded time series of the raw data is displayed in Figure 7a. Each axle of the train is clearly visible. The resolution of the strains was approximately 1 µε. The accuracy was estimated to be approximately ±3 µε. The achieved accuracy was good enough for assessment purposes and in particular for fatigue assessment using cycle counting based methods.

The raw data, however, was biased by a significant time-dependent signal. The bias was generated by switching on the strain signal conditioning device shortly before the measurement was started. Due to the resistance of the strain gage, the current flow heats the strain gage increasing its temperature and consequently its resistance. The signal conditioning (Wheatstone bridge) translates this resistance change in a decreasing voltage signal. Wired monitoring system do not show this bias because they are always operated in a temperature equilibrium state since switching on occurred long time before the first measurement started. The bias can be removed by adding a dummy gage in the Wheatstone bridge for achieving temperature compensation (2 gage system) or by a post-processing of the data (see [3] for details).

For fatigue assessment, however, only the number and the amplitude of strain cycles are usually of concern. Since the amplitude of cycles are defined by the difference of two values and the strain cycles induced by the train have a much faster time scale than the bias, the cycle counting histograms of the raw and post-processed data do not differ significantly (Figure 7b). If the accuracy requirements are not particularly tight, cycle counting using the biased raw data may already provide sufficiently good results for a fatigue assessment. This approach would allow to perform the cycle counting by the sensor nodes reducing the transmitted data to less than 1% of the raw data size. The computing of cycle counting lasts less than 0.8 seconds and is therefore very efficient.

4 Conclusions

The deployments discussed in this paper demonstrate that current WSN technology allows to perform data intensive monitoring tasks which are practically relevant. Deployments lasting many months in outdoor environments can be operated with high reliability. By optimized sensing and in-node data processing, the replacement period of batteries can be extended to several months. Despite the very limited hard- and software resources, the data quality generally matches the accuracy requirements of structural assessment.

Event driven data acquisition, which is important in practice, is still on a primitive level and requires innovative solutions. No satisfactory solution still exists for event-driven monitoring and in particular event driven strain sensing, which is very important for fatigue assessment of structures.

Further significant progress is expected to occur in the near future improving the competitiveness of WSNs. Our experiences, however, clearly demonstrate that in data intensive monitoring tasks, except perhaps for short term deployments, WSNs are not suitable for acquiring raw data as a final result. This fact, very likely, will not be subjected to change in the future.

Acknowledgments

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