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Sensor signal processing

Zero-Crossing Chirp Frequency Demodulation for Ultra-Low-Energy Precise Hybrid RF-Acoustic Ranging of Mobile Nodes

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Abstract—In this letter, we zoom in on the distance estimation in a chirp-based hybrid radio-frequency (RF)-acoustic ranging system. We present an ultra-low-power solution based on zero-crossing demodulation. We have designed an experimental prototype to validate the approach and compared the power usage, accuracy, and precision of this ranging system with a conventional method. Our measurements show that an accuracy and precision below 5 cm can be obtained for a mobile sensor node that has a lifespan of over 3794 days or ~10 years, at an update rate of 1 Hz. This constitutes a four times improvement with respect to a conventional analog-to-digital converter based indoor ranging techniques. The provided method can be extended to a system for indoor localization and opens the possibility to implement RF backscattering-based solutions for fully passive nodes.

Index Terms—Sensor signal processing, acoustic sensors, acoustic signal processing, distance measurement, low-power electronics.

I. INTRODUCTION

In the last decade, low-power microphones, processing units, and wireless communication modules have advanced wireless acoustic sensor network (WASN) applications such as urban noise nuisance monitoring [1], fall detection [2], and various localization and ranging systems [3]. These are most easily deployed as battery-powered nodes. In this light, previous studies investigated energy efficiency at each level of wireless sensor network (WSN) operations: sensing, computing, switching, and transmission [4]. Their energy conservation schemes can be divided into three subcategories: data-driven-, duty-cycling-, and mobility-based schemes [5]. In WASN, most research focuses on the data-driven schemes as sensing and processing consume significantly less energy compared to communication operations [6], [7]. We propose a combination of the first two schemes.

1) Data driven: We approach the sought-after features of the audio on a bit quantized level, hence, eliminating power-hungry analog-to-digital converters (ADCs) [8] and achieving both data reduction and computing power.
2) Duty cycling: Its contribution to the energy efficiency is twofold. On the one hand, it switches OFF the nodes to a lower power stage. On the other hand, it only obtains data during this active time, decreasing the transmitted data proportionally to the duty cycle.

In this letter, we adopt a low-power, chirp-based, hybrid signaling indoor distance measurement system. We process the changes in frequency on a binary level to calculate the distance. This decreases the complexity and energy consumption of the mobile node in comparison with conventional approaches that apply pulse compression with a high quantization level. We further experimentally confirm that the same level of ranging accuracy can be obtained with the single bit approach compared to more complex detection methods. This method has the additional benefits of enabling a higher sampling rate while maintaining the sampled data limited and the opportunity to perform faster binary calculations. The following section introduces the system design, pulse compression method, and system optimization. Section III describes the power and distance measurements. Finally, a conclusion and future work are given.

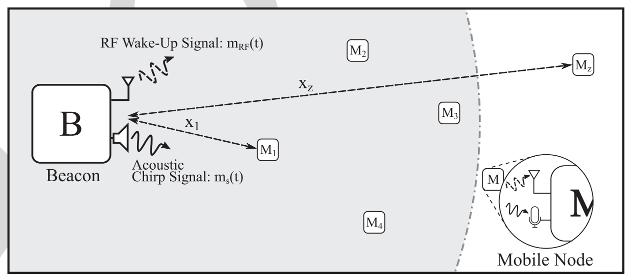

Fig. 1. Ranging system setup. The beacon periodically transmits a sound signal. All nodes are woken up synchronously on basis of the RF signal.

II. SYSTEM OVERVIEW

A. System Design

This study focuses on the hybrid ranging system that is described in [9] and depicted in Fig. 1. In essence, there are two sides. A fixed beacon sends an audio chirp and RF wake-up signal, and consequently mobile nodes all awake simultaneously triggered by the RF signal and sample audio for a limited amount of time. The ranging information is comprised in the received audio signal and depends on the distance to the beacon. Both the used chirp frequency bandwidth (Δf) and the perceived time-interval of the chirp (τ_{rx}) have an impact on the accuracy. τ_{rx} is related to the awake time of the mobile sensor nodes. The collected data are transmitted back to the base station for further processing. The approach in [9] involves limited processing at the mobile node, yet relies on an energy expensive ADC that prohibits its application in real-time energy constraint devices. We here propose a method to further optimize the mobile nodes' energy consumption.

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Autocorrelation is used to perform fast distance calculations using small datasets, as described in [10]–[13]. In linear chirps, using cross correlation is a form of pulse compression, and it can be shown [14] that the autocorrelation function of the chirp in the bandpass domain is given by

$$\varphi_{SS}(t) = A^2 \frac{\tau_{rx}}{2} \Lambda\left(\frac{t}{\tau_{rx}}\right) \sin c\left[\pi \Delta f t \Lambda\left(\frac{t}{\tau_{rx}}\right)\right] \cos(2\pi f_0 t) \quad (1)$$

with Λ a triangle function, with a value of 0 on $[-\infty, -\frac{1}{2}] \cup [\frac{1}{2}, \infty]$, linearly increasing on $[\frac{-1}{2}, 0]$ to 1, and decreasing linearly on $[0, \frac{1}{2}]$. Around the maximum, this function behaves like a cardinal sine, with a -3 dB width of $\tau' \approx \frac{1}{\Delta f_{rx}}$. f_0 in this function is the carrier frequency of the frequency band Δf. An additional advantage of using chirps signals is that they remain very well correlated over Doppler shifts [15]. Increasing τ_{rx} improves the SNR and accuracy quadratically. Here, however, the main goal is to limit the energy consumption of the nodes. We essentially restrict the receiver awake time significantly and, hence, keep the sensing and computing energy consumption low.

B. System Optimization

We optimize the system to enable ultralow power nodes by reducing the data to be processed and transmitted by the nodes. The maximum amount of acoustic data captured in the restricted wake-up time (τ_{rx}) is determined by the combination of the system's ADC sampling rate and the wireless data throughput. This is typical for WASN relying on conventional ADC's in combination with low-power, long-range subgigahertz communications. We encounter this limitation on the hardware used in our experimental validation [16]. This development board has an ADC with a resolution of 12 b and a maximum sampling rate of 200 kS/s. For an awake time (τ_{rx}) restricted to 1 ms, 2400 b are, hence, generated by the ADC. However, the maximum data throughput on the wireless link is 500 kb/s, and as a result, only 500 b can be transmitted from the mobile node to the beacon in this single millisecond. This means that for optimal sampling during the awake time, assuming 12 b/sample, the ADC sampling speed should be decreased to 41,7 kS/s. Pulse compression with this lower amount of ADC samples spreads the cardinal sine and reduces the accuracy drastically. We implement zero crossing chirp frequency demodulation [17] to enhance the accuracy in a data-efficient manner. Recent progress in high-speed, low-power digitization and memory allow to time the zero crossings of the received sound signals and to process them locally. The most common technique is to fit the binary chirp data to a parabolic equation, which, however, handles noisy signals poorly. Therefore, we here use a binary template cross-correlation technique. Previous research has also proposed ADC elimination for passive, low-power, backscatter communication and sensing [18]–[20]. These systems replace the functionality of the ADC by introducing comparators, adapting the transimpedance of a JFET or translating the voltage resolution to the time domain as a PWM signal. In this work, we propose a different approach that offers a high resolution in the time domain rather than on voltage, as we aim to precisely detect the time instants of the zero-crossings directly on the received acoustic signal. Fig. 2 illustrates both hardware implementations, namely the convenient ADC-based pulse compression technique and the newly adapted zero-crossing demodulation. In the first setup, the sound signal recorded by the MEMS is filtered and amplified through a generic op-amp. The microcontroller's internal ADC samples this signal and assembles the data in packets for efficient RF transmission. In the second architecture, a comparator is added to the development board. Here, a binary quantization is performed on the amplified and filtered audio signals through comparison with a fixed dc level. The binary data are sampled through a generic digital input/output pin at a fixed frequency of 500 kHz. Packet handling with the improved method is straightforward and does not need splitting of the samples. At the beacon side, we seek the peak of the cross correlation using a binary template based on the matching procedure of Sokal [21] instead of the Fourier transformed cross correlation. If X and Y denote n-dimensional binary vectors, let

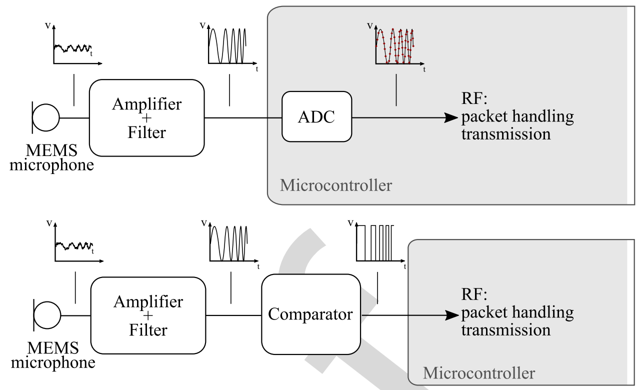

Fig. 2. System architecture for both the convenient ADC-based sampling technique and the zero-crossing modulation solution.

$$\delta_m(i, j) = \begin{cases} 1, & \text{if } x_m = i \;\&\; y_m = j \\ 0, & \text{if otherwise} \end{cases} \quad (2)$$

for $i, j = 0, 1$, and x_m and y_m are the mth elements of X and Y, respectively. Let

$$n_{ij} = \sum_{m=1}^{n} \delta_m(i, j). \quad (3)$$

That is, n_{ij} is the number of occurrences, where $X = i$ and $Y = j$. Sokal define the similarity measure as

$$\mathbb{S}_N(X, Y) = \frac{n_{11} + n_{00}}{n} \quad (4)$$

which is the ratio of the number of correctly matched 0s and 1s to the total number of binary samples. A peak-seeking procedure defines the calculated distance and is obtained by searching the index $I_{\max}$ of the maximum similarity measure:

$$I_{\max} = \arg\max(\mathbb{S}_N(n)). \quad (5)$$

The binary cross-correlation matching method based on (2) is carried out as a bit-based XNOR operation between the—locally stored—quantized, broadcasted chirp, and the binary-sampled sound signal, resulting in a lightweight implementation. A rolling window is further applied to this stored chirp to obtain binary vectors with the same length as the recorded and quantized sound signal. The matching is done by summing the bit-based XNOR results (4) without normalization to eliminate an extra operation. Finally, the distance is calculated based on the correlation maximum (5). This method can be conveniently implemented on the node and was, hence, preferred over a power-intensive Fourier-transformed cross-correlation technique. Fig. 3 depicts the results of the two correlation methods for measurements at a distance of 86 cm. The red line in these plots indicates the maximum correlation and its associated distance. With the same number of bits (41, 12 b samples), the ADC cross-correlation method has a lower pulse compression ratio, resulting in decreased accuracy and larger distance errors. Five times more bits are required to obtain similar results as the bit-based correlation method, as can

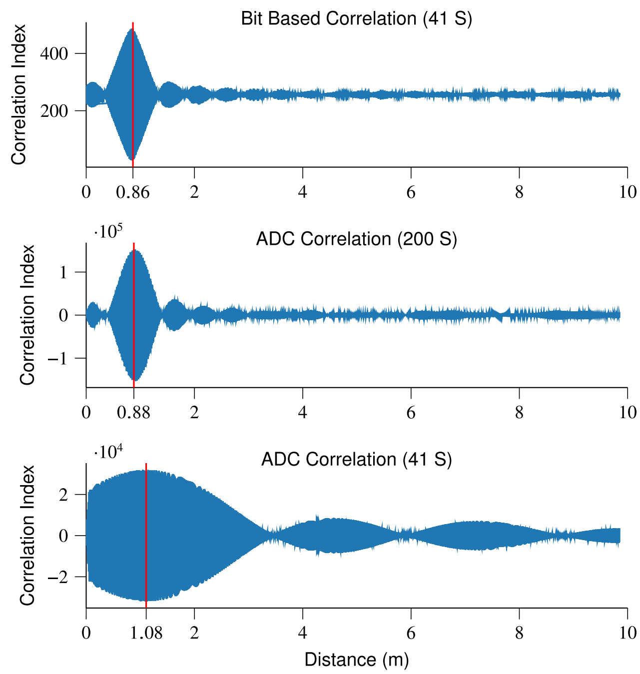

Fig. 3. Results of the two correlation methods performed for measurements at a distance of 86 cm.

be seen in the second plot in Fig. 3. In conclusion, with the bit-based correlation, we obtain similar pulse compression results with a lower amount of bits, and with a higher resolution in the time domain.

III. MEASUREMENTS

We have assessed both the power consumption and performance of the distance measurements experimentally and report thereon in the following sections.

A. Power Measurements

We implemented both the conventional ADC sampling and the zero crossing approach on the TI CC1310 development board [16] to gain insight into the possible lifespan of the mobile sensor nodes. In our experiments, we extend the analysis of the acoustic power consumption [9] with the evaluation of the energy needed for the wireless communication and processing. These power measurements were performed with a Happy Gecko with the "Energy Profiler" in Simplicity Studio at a fixed supply voltage of 3.3 V. Table 1 summarizes the power and energy consumed during the sensing, computing, and communication operations for the binary sampling method (41 samples) and the ADC sampling method (200 samples). It shows that the binary sampling method is four times more energy efficient than the ADC sampling method. This large difference results from the fact that the latter method requires a larger transmit duration in combination with the high current drawn for RF transmission. The transmit duration is directly correlated to the payload and, thus, the amount of sampling data. Note that the packet handling for the ADC sampling method is limited to splitting each 12 b samples into 2 B. Improvements could be achieved by combining two samples into 3 B, which would still result in an energy consumption that is ~180 μJ higher per measurement. The RF receiving energy consumption is the same for both techniques. Since the hardware lacks RF wake-up capabilities, an internal timer is used to leave the sleep state and force the node in an RF-listening state

Table 1. Power and Energy Comparison of the Two Sampling Techniques Implemented on the CC1310 Launchpad With External Components

	Binary Sampling			ADC Sampling		
	Power (μW)	Time (ms)	Energy (μJ)	Power (μW)	Time (ms)	Energy (μJ)
Sleep	2.4	967.5	2.33	2.4	960.9	2.31
Sampling + Pkt Hand.	3 187.8	3.9	12.43	3 465	6.5	23.39
Rx	19 239	1.0	19.24	19 239	1.0	19.24
Tx	49 170	1.0	49.17	49 170	6.25	307.31
Acoustic	1 158.6	1.0	1.16	911.1	1.0	0.91
Acoustic Sleep	6.3	999.0	6.29	6.3	999.0	6.29
Total			**90.62**			**359.45**

The supply voltage was fixed at 3.3 V dc and 1 Hz update rate.

for a single millisecond. This enables low power RF sensing, but clock drift can have a major impact on the accuracy of both sampling methods when used in longer operations. Future research should, therefore, consider possible RF wake-up systems to leave the low-power state just in time. Smaller contributions to the higher energy consumption come from the sampling and packet handling. This takes almost double the time for the ADC sampling method, while the current drawn in both cases is similar. The numbers for the acoustic power consumption are taken from previous research [9]. The only difference is that in the binary sampling method a comparator is added to the circuit, hence, the higher drawn current in an active mode. This table confirms that computational energy is insignificant compared to the wireless communication impact as for many wireless sensor nodes, confirming the statement in [5]. Calculating the lifespan of the mobile sensor node using this zero-crossing demodulation method, we estimate that it could operate 3795 days or ~10 years on 3, 1.5 V AAA batteries of 2500 mAh when performing a single measurement per second and not taking into account self-discharge.

B. Distance Measurement

We further conducted ranging measurements in a realistic environment to assess the accuracy and precision of the developed system. The experimental setup consists of a beacon and a single node, both positioned on the same height in a high reverberant (average RT60 = 1,92 s) lab room of 8.35 × 16.44 × 5.19 m. The acoustic signal at the beacon was generated by National Instruments' USB-6212 DAC and amplified before it was broadcasted by the ultrasonic Fostex FT17H speaker. The frequency range of the bandpass chirp depends on the frequency response of both speaker and microphone. In this setup, a frequency range of 20 kHz is chosen, starting from 25 kHz and going up to 45 kHz. Subgigahertz wireless communication was implemented on the aforementioned CC1310 launchpad boards. In the bit-based correlation method, the distances were calculated on the beacon launchpad board. The cross-correlation calculations for the ADC-based method were performed externally in MATLAB. Table 2 presents the mean average error (MAE) and the standard deviation (σ) for eight distances. The MAE indicates the accuracy of the measurements and is calculated by taking the absolute value of the difference between the actual and mean distance. The standard deviation specifies the precision of the system. At each of these eight distances, 100 measurements were

Table 2. Distance Accuracy and Precision Results at Eight Distances of the Two Correlation Techniques

Distance (m)		0.20	0.50	1.00	2.00	3.00	5.00	7.00	9.00
Binary 41	MAE (m)	0.005	0.005	0.012	0.016	0.007	0.048	0.028	0.623
	σ (m)	0.011	0.014	0.010	0.050	0.037	0.022	0.031	2.373
ADC 200	MAE (m)	0.056	0.018	0.007	0.032	0.019	0.083	0.476	1.165
	σ (m)	0.013	0.019	0.009	0.037	0.029	0.020	0.031	2.544
ADC 41	MAE (m)	0.040	0.023	0.010	0.061	0.084	0.193	0.242	6.676
	σ (m)	0.112	0.115	0.089	0.203	0.346	0.363	0.588	2.254

taken after tuning the transmit time of the RF wake up signal. The reference distances necessary for the MAE were measured with a Bosch GLM30 laser distance measurer. With the exception of the smallest and largest distance, the binary and ADC 200 measurements have a comparable accuracy and precision. The error stays below 5 cm for ranging under 9 m. We witness a decrease in system performance at higher distance, mainly caused by the inverse square law between the sound intensity and the distance. However, nonlinearities at the speaker frequency response can increase or decrease the distance locally (i.e., at 2 m versus 3 m). With increasing range, noise has a larger influence on the smaller received signals, and cross-correlation calculations result in several peaks with similar correlation indexes. Peak prominence methods could optimize the maximum selection to improve the distance measurements. Another cause for the lower accuracy at these larger ranges is the impact of the room temperature. Adding a temperature sensor and adapting the speed of sound in the calculations can reduce this error. Comparing the two techniques, the binary method performs best for both the smallest and largest distances. When we match the amount of transmitted data for both techniques and, thus, reduce the ADC samples to 41, the accuracy remains within reasonable boundaries (<25 cm for ranges below 9 m), but the standard deviation increases drastically, meaning that these measurements are evened out and not precise.

IV. FUTURE WORK AND CONCLUSION

In this study, we have introduced a new distance estimation method based on zero-crossing chirp frequency demodulation. Working on a smaller sample set, we are able to reduce the transmit time and, hence, energy, typically dominant in sensor networks, with a factor of 5. Measurements performed in a high-reverberant indoor environment show that both accuracy and precision of the system are below 5 cm for distances smaller than 9 m. These results are consistent with existing, high-power indoor ranging systems. In the research, the mobile sensor node has a lifespan of $\sim$10 years on three 1.5 V AAA batteries when using the proposed binary sampling method. Greater part of the energy budget is consumed by the RF wake-up. In further research, the power consumption can be drastically reduced by minimizing the listening state of the mobile node. A potential solution can be found in RF backscattering [18]–[20], where passive wireless communication at the receiver side is possible. A more in-depth study is needed to test the feasibility of such techniques. Since the maximum amount of acoustic data is determined by the RF-link throughput, a higher wireless data rate could improve these results even more. Future studies could determine the influence of bit errors and compare the speed between the cross-correlation method and the different existing matching procedures at the receiver side. Extending the existing system for 3-D localization should handle multiple-access problems in both acoustic and RF transmission medium.

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