

Energy-Efficient WSN Architecture for Illegal Deforestation Detection

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Abstract: We present an energy-efficient wireless sensor network (WSN) architecture tailored for illegal deforestation detection. Illegal deforestation is a world-wide problem which may be prevented through improved monitoring of forested areas utilizing sensor networks equipped with chain-saw detection. Additional to detection, we identify sound source localization and sensor node localization as essential features of a deforestation monitoring WSN, and analyze two possible architectures which perform sound source localization with the distributed time difference-of-arrival (TDOA) algorithm and microphone-array based localization respectively. We develop an energy model and evaluate the two architectures. Our results indicate that the microphone array based WSN requires more hardware and is more complex, but is an order of magnitude more energy efficient than the distributed TDOA WSN as it minimizes radio traffic. This improvement in efficiency enables the microphone array equipped WSN to potentially operate for over a year, enabling practical deforestation monitoring with WSNs.

Keywords: Deforestation, Acoustic Localization, Chain-Saw Detection, Energy, FPGA

1. Introduction

Illegal deforestation is a worldwide problem, with recent studies [1] indicating that between 20% and 40% of all deforestation is illegal in nature. As a direct result of illegal logging, national governments are losing significant timber sales revenue, due to competition with illegal timber. Another indirect result of illegal logging is the increase of carbon dioxide emissions, with 20% of the worldwide CO₂ emissions caused by deforestation. Affected countries are looking to implement a range of technological measures to monitor the state of the forest and discourage deforestation.

Wireless sensor networks (WSNs) are one type of such forest monitoring systems. A WSN consists of a number of sensing nodes (SNs), i.e., wirelessly connected computing devices equipped with sensors capable of delivering information about the environment while operating on an independent energy supply, e.g. batteries or solar panels. Several research projects have approached forest monitoring through use of WSNs. Forest Guardian [2] is a wireless sensor network consisting of battery-powered sensor nodes fastened to trees, communication routers which assist in long-range communication, and an aggregation point which communicates WSN data to a far-away WSN user. The

Forest Guardian WSN collects acoustic data, in order to detect the sound signature of deforestation activities, e.g. chain-saw noise. Similar solutions are proposed in other work, with differences mainly centered on the efficient transmission of data and detection of the sound signatures [3, 4]. More recently, commercial take-up of WSN-based deforestation monitoring has begun. Rainforest Connection¹ is an implementation of the Forest Guardian concept utilizing cellular phones as sensor nodes and solar panels for battery charging. In the proposed WSN architectures, nodes have to be individually strapped to trees, and their position is selected carefully to permit nodes to overlap in their sensing and communication ranges.

We acknowledge the valuable contributions of previous work and accept that acoustic detection of illegal deforestation is the only feasible approach currently in existence. However, we feel that previous work has only touched upon important pieces of the deforestation monitoring WSN puzzle in isolation, without a focused effort to define a WSN architecture which is effective overall, both in cost and monitoring accuracy. This paper presents an overview of existing WSN techniques for illegal

¹ <https://rfcx.org/>

deforestation detection and proposes a self-organizing wireless sensor network concept based on a clearly defined monitoring use-case: monitoring the legality of activities in a licensed logging area. The proposed wireless sensor network may be deployed more easily than existing WSNs to a forested region, via drone air-drop. During deployment, each sensor node identifies their position and spatial orientation. After deployment, the WSN monitors the forest for characteristic illegal deforestation acoustic signatures, such as the sound of chain-saws, and identifies the position of the logging activity within its range, enabling WSN operators to determine if suspicious activity is taking place. Energy and cost considerations guide the development of the proposed WSN sensor node and architecture, maximizing the practicality and life-time of the WSN.

2. WSN for Illegal Deforestation Detection

2.1. Use Case and Performance Metrics

We approach the design of an efficient sensor node by first establishing a use-case for the WSN. Clearly, not all forested areas may be monitored, especially remote areas, as it would require too many sensing nodes. Indeed, remote areas are rarely targeted for illegal logging because of the difficulty of transporting the cut wood in the absence of roads. The monitoring problem becomes practical by focusing on the illegal logging performed by licensed loggers which either cut in restricted areas such as steep slopes, riverbanks and water catchments, perform clear-cutting (total deforestation of an area) despite being issued a license for selective cutting, or cut outside of the authorized logging season. Loggers may also report to the authorities less volume than was actually cut. Local corruption often aids loggers in hiding the mishandling of a license.

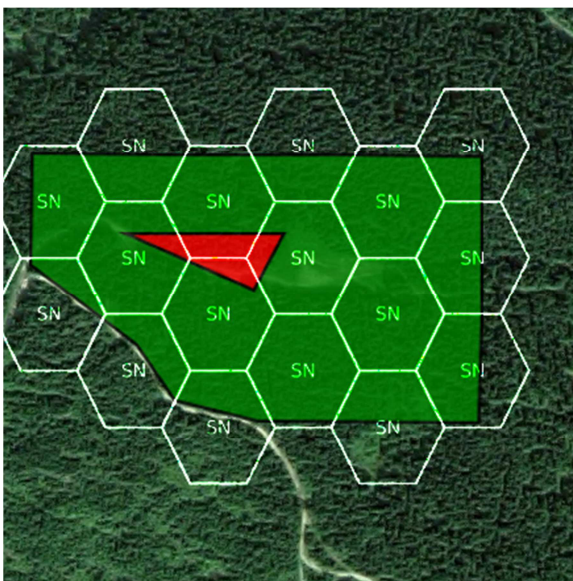


Figure 1. WSN covering a forest exploitation.

We can therefore concentrate on the use-case of monitoring a licensed wood exploitation to ensure the licensee does not violate the terms of the allocated license as above-mentioned. The example in Figure 1 illustrates a 9 ha / 22 acre area of forest, green indicates licensed logging areas centered on an access road, while red indicates a steep slope where logging is prohibited. Also illustrated is a theoretical WSN coverage assuming a sensor node has approximately 50 meter range. Sensor node (SN) locations are marked.

In this monitoring scenario, SNs are responsible with the detection of logging activity within their range, discriminating from other noises. Within the area monitored by a SN, restricted and free-to-operate zones may exist, such as the restricted zone indicated in red, in Figure 1. For SNs which lie on the border of a licensed exploitation, restricted zones are everything outside of the licensed exploitation. Nodes must have the capability of localizing the source of deforestation activity within their operating range, relative to their own position, in order to determine if the deforestation occurs within a restricted zone. If so, nodes must provide to the authorities the coordinates of the suspicious activity, converting the relative position of the deforestation noise to absolute GPS coordinates. This in turn depends on the SN's capability of localizing themselves on the ground. If all these conditions are met, the WSN may be utilized to protect the restricted zones from logging activity or determine if logging is unusually concentrated (sign of clear-cutting) in non-restricted zones.

2.2. Practical WSN Design Guidelines

Any design of a practical WSN for deforestation monitoring must aim to minimize the deployment and operation cost of the WSN, which in turn is expected to maximize the probability of the WSN actually being utilized in the field. We identify the main sources of cost, and list them chronologically in the life-time of the WSN:

- per-SN manufacturing cost, which depends on the SN complexity; costs per-SN decrease when manufacturing large numbers of nodes
- per-SN deployment cost, which depends on the complexity of the deployment process
- per-WSN cost, which depends on the number of SNs; increasing the range of the SN means fewer nodes are required therefore the WSN is less expensive overall;
- operational cost, which are the costs incurred by the operation of the WSN over its lifetime, and mainly consists of SN replacement costs when nodes go offline because of exhausted energy supply or damage.

We therefore focus on the minimization of these costs while achieving the functional requirements set out by the use-case. SN cost may be minimized by implementing the functionality of the SN with minimal hardware complexity. Whenever possible, the various functions of the SN must share hardware.

With regard to deployment cost, we propose from the onset that manual deployment is not feasible. The example in Figure 1 would require 17 sensors to be placed by hand in thick forest and possibly steep terrain, requiring at least two persons to

carry the equipment and perform the work, for a total of 2-4 person-days effort. Instead, we propose to air-drop sensor nodes by drone. Commercial drones can be programmed to fly on predetermined GPS paths and perform actions at specified points, such as dropping a sensor node. However, the exact final position and spatial orientation of the node post-drop is undetermined, since it may be carried by the wind, bounce off trees or slide down slopes. Therefore, drone deployment is only possible if the nodes may localize themselves.

To reduce operational cost, the SN design must maximize the computational energy efficiency of the SN individually and of the WSN overall. A focus of attention is the minimization of radio traffic required for WSN operation. In [5] it is demonstrated that communication energy costs for WSN nodes is at least an order of magnitude larger than computation and sensing energy costs. Radio-less solutions to the functional requirements of the SN are therefore preferable.

3. Previous Work

In order to meet the WSN functional requirements, this section explores and evaluates existing work for all key areas of the proposed WSN: sound source identification, sound source localization, and sensor node localization. The aim of this analysis is to select a sub-set of techniques useful for our use-case and guide architectural development in Section 4.

3.1. Chain-Saw Detection

In [4] a light-weight approach to chain-saw identification is proposed, based on the auto-correlation of 256-sample blocks of audio signal. The authors refer to this method as Lightweight Acoustic Detection (LAC). Signal energy is utilized, as well as pitch and pitch stability measures computed from the autocorrelation of the signal. These measures are chosen because chain-saws are much noisier than forest ambient sound, have distinctive pitch signatures and have good pitch stability. LAC executes in real-time on a WSN sensor node based on the ATmega128RFA1 microcontroller. The reported accuracy of detection is up to 85%.

In [2] and [6], an algorithm called Normalized Peak Domination Ratio (NPDR) is utilized, which utilizes only the signal spectrum and noise energy. NPDR looks for an overlap between the signal and pre-computed reference peaks in the spectrum, and also for a sufficiently high concentration of signal energy in the spectral vicinity of the reference peaks. Evaluation of NPDR on 1024-sample blocks of signal indicates over 99% accuracy in quiet room conditions on a range of sounds. NPDR runs on a PC and the authors indicate (but do not demonstrate) the possibility of executing NPDR on smartphones. Of the two algorithms, NPDR has better accuracy and LAC a slightly simpler structure which may result in a more efficient implementation. A selection between the two may only be made by taking into account their integration into the WSN framework and the efficiency of their implementation, analyzed in Section 4.

3.2 Sound Source Localization

Sound source localization (SSL) has been achieved for single-microphone SNs in previous work through the use of distributed time difference of arrival (D-TDOA). In D-TDOA, nodes synchronize their internal clocks and sample a reference sound at a pre-determined moment in time. Because it has already been established through synchronization that the sampling is simultaneous, any difference in audio signal phase at the sensing nodes is caused by differences in relative position of the sound source to the respective SNs. If the geometry of the WSN is known a priori, then the individual measurements are aggregated to determine the position of the sound source relative to the WSN. D-TDOA requires that time re-synchronization, hence radio communication, and must occur before each SSL event to compensate for drift in SN timers. Following signal acquisition, the data must be aggregated for the SSL to be computed. The WSN incurs an energy consumption penalty for these communication events.

A different approach to sound source localization has been explored in [7] utilizing microphone arrays. We refer to this method as Array TDOA (A-TDOA). In A-TDOA, each SN is equipped with an array of microphones arranged in a fixed geometry. To obtain positioning in a 2D plane, a planar symmetrical geometry is best suited, such as placing the microphones on a circle. Delay-and-Sum (DS) [8] is algorithm utilized in [7] for sound direction estimation, although more sophisticated algorithms exist [9]. The simultaneous multi-microphone sampling in A-TDOA necessitates a FPGA to buffer and process the audio samples, while the MCU is required only for control.

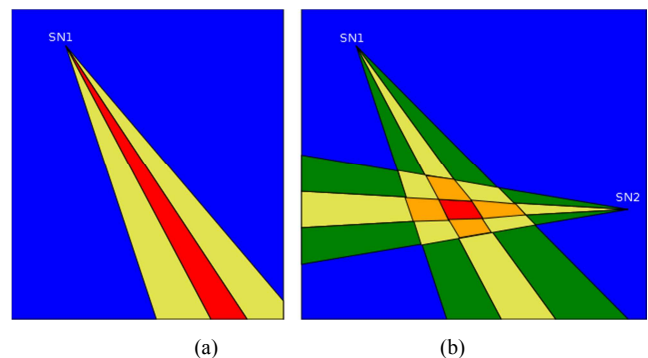


Figure 2. A-TDOA illumination.

Two or more A-TDOA direction measurements by separate WSN nodes may be aggregated as in Figure 2 in order to increase the localization accuracy if needed. A single SN can only determine through A-TDOA the probability that a sound source is located in a certain direction relative to the SN. This may be illustrated visually through the illumination diagram in Figure 2a. Red illustrates high probability of sound coming from the respective direction; yellow denotes medium probability, while blue represents low probability. Adjacent SNs with overlapping sensing ranges may superimpose their illumination diagrams by summing the probabilities, resulting in a more accurate localization as demonstrated by Figure 2b.

The cost of the increased localization accuracy is energy expended for SN communication. The implication on the WSN architecture is that accurate localization requires SN range overlap.

It must be noted that A-TDOA can only determine the direction of a sound source relative to the SNs microphone array. In order to obtain an absolute illumination diagram such as Figure 2a, A-TDOA requires that the sensor array orientation, relative to true North, be known at each node. Three-dimensional positioning requires in addition that the orientation relative to true vertical be known. Therefore, for A-TDOA there must also be some way for the SN to determine the absolute orientation of the microphone array, preferably without extra electronics such as accelerometers and magnetometers. A solution is provided in Section 3.3.

Localization by A-TDOA avoids the need for WSN time synchronization. Conversely, on-node computation is required for A-TDOA to determine the sound direction. Both A- and D-TDOA require data aggregation between nodes to determine the sound source accurately; however A-TDOA is capable of obtaining a certain measure of localization without SN communication. In some cases, such as the border SMs in Figure 1, knowing the general direction of the sound source is sufficient to discriminate between legal and illegal deforestation activity.

3.3. Sensor Node Localization

Reference [10] gives an overview of some of the more popular WSN localization techniques. The most obvious choice for WSN localization is GPS. However, GPS is an expensive piece of equipment. Alternatives to GPS for general-purpose WSNs have centered on radio measurements such as received signal strength (RSS) to evaluate the distance between sensor nodes [11]. In a comparison of RSS to GPS localization, it was found that RSS is less accurate than GPS. Both methods are sensitive to environmental factors such as tall trees or obstacles.

Since our proposed WSN has acoustic sensing capabilities, it is also possible to determine the positions of the sensor nodes utilizing acoustic beacon localization (ABL) [12]. Indeed, ABL is the inverse of D-TDOA: knowing the position of a signal source, one may determine the geometry of the sensor network from differences in time-of-arrival of the sound at microphone-equipped SNs. The sound source is an acoustic beacon emitting a pre-determined acoustic pattern which is easily recognized by the nodes. The absolute distance of nodes to the beacon may be determined by measuring time of flight from the beacon to the individual nodes.

4. WSN Architecture

4.1. Synergy Analysis

Section 3 provides a short-list of techniques to perform chain-saw detection, sound source localization and SN localization. Of these, the most synergistic combination must be found, i.e., one that requires the least amount of hardware

to implement and consumes the least amount of energy to operate.

We identify the following synergistic relationships between the techniques described in Section 3.

4.1.1. ABL and D-TDOA

As ABL is effectively the reverse of D-TDOA, it is evident that much of the underlying algorithms and hardware are common to both techniques. This includes the time synchronization routines and the data aggregation. This makes the techniques easy to implement together.

4.1.2. ABL and A-TDOA

In A-TDOA, it is necessary to establish the orientation of an on-node microphone array prior to sound source localization. ABL enables this orientation to be established without the use of an accelerometer or magnetometer.

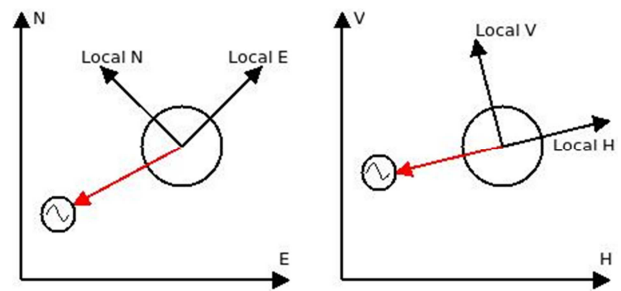


Figure 3. Acoustic Beacon Localization.

To illustrate this fact, consider that the WSN has been localized with ABL or some other technique, and that each SN has a spherical sensor array oriented randomly in 3D space, presented in Figure 3 as two projections in the horizontal and vertical planes. The location of the acoustic beacon is also known by e.g., GPS. When the acoustic beacon emits, each SN determines the sound direction relative to its own array, depicted in red in the figure. The expected sound direction relative to true North and true vertical may be calculated from the position of the beacon and of the SN. The difference between the actual direction and the computed A-TDOA direction on each SN is caused by the misalignment of the sensor array, and may be stored on each SN to correct subsequent A-TDOA measurements in software.

4.2. Sensor Node Configuration

We base our SN design on the Mica2 [13], an extensible sensor network hardware platform, equipped with an Atmega128/L [14] processor and a CC1000 [15] radio. Table 1 summarizes the extra hardware requirements, and the radio traffic required by each WSN feature. A-TDOA is listed twice because some hardware requirements may be eliminated by its combination with acoustic beacon localization, as discussed in Section 4.1. By combining NPDR with D-TDOA and RSS, the SN required functionality may be implemented with the addition of a single microphone to the Mica2. We shall refer to this configuration as MinH (minimal hardware), as listed in Table 2. MinH is representative of WSNs described in previous work [2]. We also consider a configuration consisting

of NPDR with A-TDOA and ABL which minimizes radio traffic for sound source and SN localization. We shall refer to this configuration as MinR (minimal radio traffic). We shall compare MinH and MinR with regard to energy efficiency.

Table 1. Comparison of WSN Techniques.

Function	Technique	Hardware	Radio Traffic
Chain-Saw Detection	NPDR	Microphone	-
	LAC	Microphone	-
	D-TDOA	Microphone	Medium
Sound Source Localization (SSL)	A-TDOA (w/o ABL)	Microphone Array, Accelerometer, Magnetometer, FPGA	Low
	A-TDOA (w/ ABL)	Microphone Array, FPGA	Low
Sensor Node Localization (SNL)	GPS	GPS Receiver	Very Low
	RSS	-	Very Low
	ABL	Microphone	Very Low

Table 2. Proposed WSN Configurations.

WSN Configuration	Detection Technique	SSL Technique	SNL Technique
MinH	NPDR/LAC	D-TDOA	RSS
MinR	NPDR/LAC	A-TDOA	ABL

For the MinR microphone array, we select the simplest symmetric configuration in three dimensions, which is a cube with microphones at the corners. The 3D configuration is required because of the necessity for the array to function in any orientation post-deployment, and to localize a sound source directly above it (the acoustic beacon on the deployment drone) during SN localization with ABL. The 8-microphone array enables the sound source to be localized to within one quadrant. In our analysis, both configurations utilize MEMS digital microphones, because of their compact nature and low energy consumption.

4.3. WSN Architecture and Operation

In the following we describe operational scenarios for a detection event for each of the three configurations under analysis, in order to determine the amount of radio traffic and computation taking place in the sensor nodes and the WSN overall. We also determine the effects of the SN configuration on the WSN architecture.

4.3.1. MinH

The MinH configuration performs SSL by measuring TDOA between two nodes. The implication is that each point in the monitored area must fall within the sensing zone of at least two SNs. Upon chain-saw detection, SNs must broadcast to the neighboring nodes and determine which of the neighboring SNs have also detected the chain-saw noise. These nodes form the TDOA set, and the SNs determine by an algorithm which is the master node of the set, which is to perform the TDOA computation. The SNs then proceed to synchronize their internal clocks in preparation for a SSL.

After synchronization, the acoustic field is sampled again,

simultaneously, by all SNs in the TDOA set. The sampled data is transmitted to the master node, which computes the cross-correlation between each pair of sampled signals, and calculates the SSL. The SSL information is reported to the central hub.

4.3.2. MinR

The MinR nodes, upon successful detection of chain-saw noise, compute the SSL locally, utilizing a FPGA for sample buffering, and report the information back to the central hub. Based on the SSL accuracy requirement, nodes may be placed closer or farther apart, such that each point is covered by a single, or at least two SNs respectively. Hybrid placement strategies are also possible, with denser placement near restricted areas.

5. WSN Energy Analysis

Energy is expended in a WSN mainly through communication and computation, but also through sensor operation [5]. In order to estimate the operational energy expenditures of the MinH and MinR configurations, we assign energy costs to communication and computation activities based on component datasheets and previous research. Table 3 summarizes the hardware, processing, memory and communication characteristics of the Mica2 and its operating system, TinyOS [16].

Table 3. Energy Model Parameters.

Parameter	Description	Value
F_{MCU}	uC Frequency	8 MHz
V_{DC-MCU}	uC Voltage	3 V
I_{S-MCU}	uC Sleep Current	15 μ A
I_{A-MCU}	uC Active Current	8 mA
C_B	Battery Capacity	2500 mAh
$V_{DC-MEMS}$	Microphone Voltage	1.8 V
I_{A-MEMS}	Microphone Active Current	0.6 mA
P_{A-FPGA}	FPGA Active Power	21.8 mW
V_{DC-R}	Radio Voltage	3 V
S	Radio Link Speed	19200 bps
P	Maximum Packet Length	256 Bytes
L_P	Radio Preamble Length	100 ms
I_{RX}	Radio Receive Current	9.6 mA
I_{TX}	Radio Transmit Current	16.5 mA

For audio sensing, both configurations utilize digital MEMS microphones. We select the MP34DT01 [17] digital MEMS microphone to serve as a discussion vehicle, and list its supply voltage $V_{DC-MEMS}$, and its active (sampling) current I_{A-MEMS} . To estimate the power dissipated by FPGA processing, we selected the MicroSemi Igloo2 FPGA as a discussion vehicle, and utilized the Microsemi Power Estimator (MPE) to obtain the active power estimate P_{A-FPGA} . The MPE parameters are as follows: Igloo2 M2GL010 FPGA device, package 400VF, Typical Commercial process, Core voltage 1.2V, 10 MHz clock fanning out to 6000 Flip-Flops, and 9000 Look-up Tables. Activity rates were set to default.

Radio parameters (link speed, maximum packet length, preamble length) are extracted from the CC1000 datasheet and the TinyOS wireless link parameters. We have selected maximum values for speed and packet length.

Table 4. Energy of WSN Activities.

Activity	Energy Formula	Energy Value [uJ]
Transmit N-bit Packet	$V_{DC-R} * I_{TX} * (L_P + N/S)$	$4950 + 2.58 * N$
Receive N-bit Packet	$V_{DC-R} * I_{TX} * (L_P + N/S)$	$2880 + 1.5 * N$
Compute 1 Instruction	$V_{DC-MCU} * I_{A-MCU} * (1/F_{MCU})$	$3 * 10^{-3}$
Sample 1s of Audio	$V_{DC-MEMS} * I_{A-MEMS}$	1080
Process 1us of Audio on FPGA	$P_{A-FPGA}/10^6$	21.8

In our analysis we ignore the energy expended for WSN localization as it is a one-time (deployment only) event which does not significantly affect the lifetime of the WSN. Table 5 presents an evaluation of the computational intensity of LAC and NPDR, as executed on a microcontroller. Complex multiplications have been counted as six real operations (four multiplications and two additions). We have taken into account the energy required to sample the signal block and compute the signal energy, autocorrelation and FFT on the audio data. NPDR proves to be most efficient with regard to total amount of operations per signal block, but consumes four times more energy for sampling, because of the larger block size. Overall, the energy comparison is very close, but favors NPDR, which we shall utilize as detection algorithm for all subsequent energy analysis of the MinH and MinR WSN configurations.

Table 6 presents an evaluation of the computational effort and communication required to perform sound source localization with D- and A-TDOA respectively. For A-TDOA the evaluation is based on an 8-microphone array, while D-TDOA is evaluated in the context of a triangle of SNs working together to perform SSL.

Table 5. Computation Effort and Energy for Chain-Saw Detection.

Algo.	Block Size [samples]	Effort [10^3 Instructions]				Energy [uJ]
		Signal Energy	Auto Corr.	FFT	Total	
LAC	256	-	130	-	130	417
NPDR	1024	2	-	30	32	206

Table 6. SSL Computation and Communication.

Algorithm	Computation [instructions]	Communication [bytes]	
		Synchronization (Tx/Rx)	Aggregation (Tx/Rx)
D-TDOA	$6.5 * 10^6$	1.33/2.66	1200/1200
A-TDOA	-	-	4

The listed D-TDOA synchronization communication requirement is the average number of bytes transmitted or received by each of the 3 SNs involved in D-TDOA. In this case we consider 4 bytes sufficient to hold a time reference for synchronization. One SN (the master) transmits the 4-byte reference time, while the other two receive. A-TDOA does not require time synchronization.

The aggregation data transfers for D-TDOA involve the

transmission of the captured audio data in full to the master D-TDOA SN. Assuming the nodes are 50 meters apart, and rounding the speed of sound to 1000 km/h, then the maximum phase offset of the sound at the three nodes is 180 ms. At a sampling rate of 10 KHz and a sample size of 8 bits, the minimum a SN must capture and transmit the the master SN 1800 bytes of audio data. Conversely, the data aggregated for A-TDOA is not the raw audio samples, but instead the direction information, which may be expressed in as little as 4 bytes, sent by the SN. We ignore packet headers and other meta-data for this analysis.

Computationally, both TDOA variants perform all-to-all correlations between sensor data. In D-TDOA, 3 sensors require 3 correlations to be performed on blocks of 1800 samples. The processing takes place on the master SN only, therefore we average out the computation to the three SNs involved in D-TDOA.

The 8 sensors of A-TDOA require 28 correlations. However, A-TDOA processes much smaller blocks than D-TDOA. This is because the A-TDOA sensors are much closer, approximately 10 cm, a distance traveled by sound in 36 microseconds. In the case of A-TDOA, the samples are buffered and processed inside a FPGA. Therefore no MCU processing takes place, but energy is consumed by the FPGA which must be active during sampling. The processing of the sampled data takes place at 10 MHz, a much higher frequency than the sampling rate, therefore the FPGA processing time is much smaller than the sampling time and will be ignored for the subsequent energy analysis.

Table 7 lists the energy consumption of the MinH and MinR configurations. Chain-saw detection consumes the same because NPDR is utilized in both. SSL sampling energy reflects the larger number of samples required for MinH, which utilizes D-TDOA. Even though MinR samples from 8 microphones, the energy is less overall because the microphones stay active for less time.

Table 7. SN Energy.

Energy Component	Energy Consumption [uJ]	
	MinH	MinR
Chain-Saw Detection	206	206
SSL Sample	195	35
SSL Compute	19500	87
SSL Communication	45309	5032
Total	65210	5360

From this energy analysis it becomes clear that MinR is preferable from an energy efficiency point of view, with NPDR as detection algorithm. The largest energy component in the case of MinH is communication, which consumes 75% of the total energy required to perform the deforestation detection function. Evidently it is not feasible to transport the large amounts of data between nodes. The D-TDOA processing itself is also expensive energetically. If the extra costs and complexity of a microphone array are tolerable to the WSN user, then MinR is capable of extending SN life-time by an order of magnitude in operational conditions. If we

estimate that a detection and SSL occur repeatedly every 10 seconds, the 2500 mAh batteries are capable of sustaining the MinR SN for over a year.

6. Conclusion

This paper fills the knowledge gap between existing work and practical forest monitoring WSNs by defining a clear use-case, and a cost-effective deployment strategy. Through analysis of existing algorithm for chain-saw detection, sound source localization and WSN localization we identify an energy-efficient WSN architecture suitable for deforestation monitoring, within the confines of the use-case, which makes use of an on-node microphone array to determine sound source locations and acoustic beacon localization for localizing the SN itself. Despite its increased sensor node cost relative to alternative architectures, we demonstrate that our chosen architecture is the most effective overall at maximizing the WSN life-time and utility. The energy model utilized in this work must be refined through practical implementation of the WSN and measurements of its performance in real-world forest monitoring scenarios. Continued research in this area is the key to solving the problem of illegal deforestation.

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