Radio-Based Trail Usage Monitoring with Low-End Motes

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***Abstract*—Outdoor automated people counting is essential to the proper management of recreational and protected areas. We present a solution for radio-based people counting that employs low-end motes to detect the signature of shadowing events left by humans on the RF signal as they interrupt the line-of-sight path between a radio transmitter and a receiver. Our solution can be implemented with devices with a reduced form factor, requires little computing power, and provides a satisfactory performance at a low energy cost. We illustrate our implementation on TelosB nodes and present an extensive set of results from a real-world deployment.**

***Keywords*-wireless sensor networks, shadowing, experiments, deployment, people counting, TelosB**

I. Introduction

In parks and recreational areas, trail usage information is very important for a rational allocation of funding resources and manpower. Oftentimes, managing authorities acquire usage information by visual inspection, which can only provide qualitative data affected by an inherent temporal bias. The use of automated counting systems enables a more systematic monitoring of key segments of the network. An efficient automatic counting system must be small, inconspicuous, flexible, easy to install/uninstall/reinstall, and accurate. Funding allocation for trails is particularly critical in Switzerland, which has an extensive network of 60,000 km of maintained hiking trails that criss-cross its relatively small landarea (41,284 kmq), most of which is effectively used for recreation. Local authorities and organizations invest lots of time and money in trail maintenance to keep the network up to the high standards that its users have come to expect.

In this paper we describe a system for radio-based trail monitoring designed for and built with low-end sensor nodes. The system is based on the harvesting of motion information from the RF signal based on our previous work on sensorless sensing [1]. We present the design and implementation of the system and show various performance metrics measured during a real-world deployment on hiking trails in Southern Switzerland.

II. Related Work

A. People Counting Solutions

There exist various viable solutions for outdoor people counting, as reported in several extensive surveys [2] [3] [4]. There are two main categories: mechanical devices and electronic devices. Mechanical systems are generally easy to hide (systems can be buried underground) and therefore basically vandal-proof, but their installation is time-intensive and inflexible, and they are subject to wear-and-tear. Common solutions include piezoelectric underground pressure counters, pneumatic tube counters (rubber tubes that are laid on the ground and detect changes in air pressure when the tubes are compacted), and acoustic slab sensor (one or more underground slabs sensitive to micro-variations in pressure are used to detect footsteps). In [5], mechanical automatic counting is employed to keep track of the visitors to the Swiss National Park. The authors employed eight acoustic slab sensors and reported an error rate of 5% obtained after a laborious calibration process.

There exist various kinds of electronic solutions. Passive infrared systems employ lenses that detect radiations emitted by people and animals. They are relatively cheap and energy-efficient, but are affected by overly high false alarm rates. They are not suitable to outdoor operation because they are affected by a significant performance degradation when their lenses start to get obstructed by dirt. Active infrared systems consist of a pair of terminals, with a transmitter emitting several infrared beams and a receiver checking which beams are obstructed. These systems are also affected by high false alarm rates and are significantly more expensive than their passive counterparts. This technology was pioneered for purposes of trail monitoring by the United States Forest Service. Solutions based on video-image processing are also available, but are typically power-hungry and hard to camouflage. Body heat detectors (pyrodetectors) are designed to detect variations in the ambient air temperature: a lens sensitive to the infrared radiation emitted by the human body detects each time a person passes. They become rather inaccurate in cold weather due to people wearing more layers of clothing. They are typically mounted on 1.5m high posts to pick up heat from the head and upper chest area. They do require lots of maintenance, because they must be kept clean. Finally, radio-based solutions consist of a transmitter-receiver pair, with a receiver continuously monitoring the RSS (Received Signal Strength) to check for obstructions of the Line-of-Sight path from the transmitter. Radio-based solutions require little maintenance and offer an excellent tradeoff between counting accuracy and energy consumption. They are rugged, easy to install, and generally well-suited to outdoor applications. Radio-based commercial products for outdoor people counting are already commercially available through Chambers Electronics UK [6]. Our goal in this work is to build a radio-based system using mote-class devices and leverage their programmability to explore the parameter space of radio-based motion detection, which would not be possible with a commercially available system. In our previous work [1], we studied radio-based motion detection with mote-class devices, and in this paper we apply some of the lessons learned in that study.

B. RSS-based Information Harvesting

Radio-based people counting means harvesting information from the RSS. Common flavors of RSS-based information harvesting include link estimation [7], mobility detection [8], intrusion detection [9], and localization. The RSS is affected by the vagaries of wireless propagation and of the radio hardware, so some form of signal processing is generally applied. In energy-constrained sensor nodes, the most common form of RSS processing is represented by Exponentially Weighted Moving Averaging (EWMA) filters, used in [7] and [10] for link estimation. RSS-based motion detection is the topic of [11], where schemes based on spectral analysis are proposed for high-end nodes (such as laptops). Such schemes, however, are too computationally intensive for low-end sensor nodes. In the aforementioned work on radio-based motion detection [1], low-complexity techniques expressly designed for low-end sensor nodes are presented and evaluated experimentally. Our work has been applied to motion detection in [12], whose approach takes the RSS Frequency Distribution into account, similarly to our approach in this paper. The form of RSS processing employed in this paper is essentially peak detection. In the literature, there is a significant amount of work on peak detection. A notable approach is the Continuous Wavelet Transform [13], but it is too computationally intensive for a low-end sensor node. Other approaches come from machine learning, such as neural networks, statistical classifiers, Bayesian networks, or tree classification algorithms. While many of these algorithms can be efficiently implemented on sensor nodes, they all require a-priori training data set, where data is pre-classified and fed into the system to teach it to recognize the desired patterns. Such an approach is impractical for our application, as it would require re-training the classifier for each deployment site. We therefore center our RSS processing around a simple scheme that proves to be very effective for our specific application.

III. Detection of Shadowing Events

A. Body Shadowing

Obstacles between a radio transmitter and a receiver cause a physical phenomenon known as *shadowing* [14] [15]: the obstacles attenuate the signal power through absorption, reflection, scattering, and diffraction. Human bodies passing in between two wireless terminals act as moving obstacles and cause *body shadowing* events that leave a significant signature on the received signal strength (RSS). The goal of radio-based people counting is to leverage the shadowing signature of the human body on the RF signal to count people. Our specific goal is to perform radio-based people counting using the TelosB mote, which has a small form factor, can be easily ruggedized and camouflaged for our outdoor application, and is equipped with a low-power radio (CC2420) with a relatively low energy consumption. On the flip side, motes offer limited computing power, and their low-power radio is notoriously exposed to the vagaries of wireless propagation [16]. In the remainder we assume that, when node i transmits to node j, nodes i and j form a directional wireless link that we denote as (i, j).

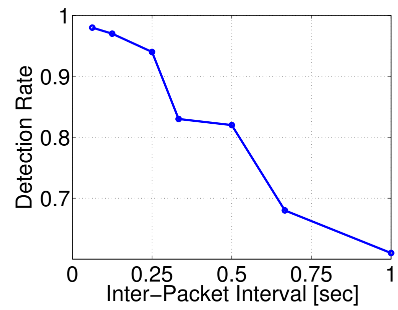

Figure 1. Detection Rate as a function of the Inter-Packet Interval (IPI), which may be viewed as our sampling interval. An IPI of 0.25 sec offers the best compromise between energy consumption and detection reliability.

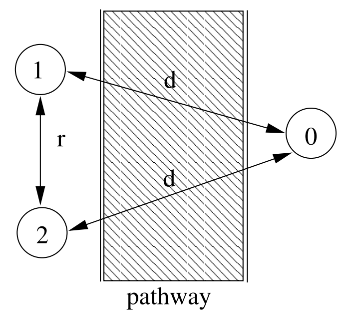

Figure 2. Layout for the people counting application. Support nodes 1 and 2 are located across the pathway from lead node 0.

B. Sampling in Time and Space

Our solution requires the motes to continuously exchange packets at a constant Inter-Packet Interval (IPI) and, for the sake of reduced energy consumption, interleave their communication with sleep modes that enable them to shut down their radio. The choice of the IPI presents a tradeoff between energy consumption (lower at lower IPIs) and

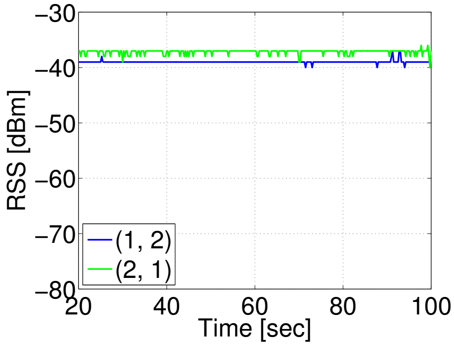

Figure 3. Link pair (1, 2) and (2, 1) is a side-link pair not meant to be used for detection.

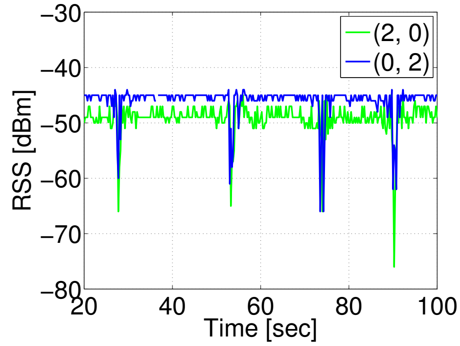

Figure 4. Link pair (2, 0) and (0, 2) is an example of a stable link with a stable baseline level.

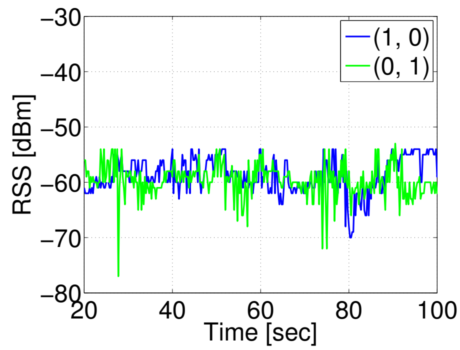

Figure 5. Link pair (1, 0) and (0, 1) is an example of an unstable link with a very noisy baseline level.

detection reliability (also lower at lower IPIs), and Figure 1 shows that the best compromise is achieved at an IPI of 0.25 sec (*i.e.*, by having the nodes exchange 4 packets per second). The choice of the number of nodes also presents the same tradeoff: throwing in more nodes means having more links to detect shadowing events on (like IPI controls the time sampling accuracy, the node count controls the spatial sampling accuracy). However, more transmitters also means longer on-intervals for the receivers, so we have the same tradeoff between energy consumption (lower with fewer nodes) and detection reliability (also lower with fewer nodes). The choice of the node count is further affected by the overall cost of the system and the ability to disguise the system on the field; for all these reasons, we settled on the layout shown in Figure 2, with 3 nodes arranged as a triangle around the pathway, so that 4 links out of 6 (*i.e.*, (0, 1), (1, 0), (0, 2), (2, 0)) can be employed for shadowing detection. To enable duty-cycling, the nodes need to be synchronized so that their radios can go into sleep mode concurrently. For the prototype described in this paper, we limit ourselves to a coarse form of time synchronization whereby at each IPI nodes 1 and 2 align their clocks to node 0's reference broadcasts, enabling the 3 nodes to achieve a duty cycle of 15-20% (which could be significantly reduced with a finer time synchronization scheme).

C. Impact of Path Loss and Fading: Link Stability

Shadowing is not the only RF phenomenon that impacts radio propagation. The other two key phenomena are the path loss (the dissipation of the power radiated by the transmitter over the distance traveled to the receiver) and multipath fading (the RF signal arrives at the receiver by way of multiple paths that may add up destructively or constructively). The path loss affects the geometry of the layout in Figure 2, and, specifically, the distances d and r. We determined experimentally that, for best results with our specific hardware, d should be below 2 meters, or else the attenuation of the RF signal by way of the path loss becomes too significant and the footprint of shadowing cannot be detected properly. The geometry, however, is even more affected by multipath fading, which in our case is mainly static fading [17] (given that the nodes are stationary).

Our empirical results show that, even at the maximum transmit power of the TelosB platform (0 dBm), the footprint of shadowing and the footprint of static fading are often closely coupled. There exist links, however, that are hardly affected by static multipath fading; qualitatively, the RSS level of such links experiences a reduced fluctuation level, and a quasi-constant baseline RSS value can be measured in the absence of link disturbances. Figure 4 shows an example of such links, corresponding to link pair (2, 0) and (0, 2) in an experiment with the layout in Figure 2; we will refer to such links as *stable links*. On the other hand, there exist links that are heavily affected by static multipath; for such links, which we will refer to as *unstable links*, there exists no recognizable baseline level even in the absence of disturbances, as can be seen in the example in Figure 5, which corresponds to the link pair (1, 0) and (0, 1) in Figure 2. As a term of comparison, we also show a typical example of a side-link pair (not meant to be shadowed by construction) in Figure 3, which corresponds to the link pair (1, 2) and (2, 1) in Figure 2.

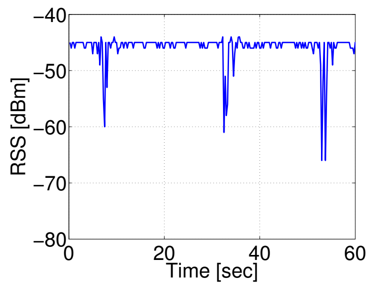

Figure 6. A one-minute slice of the RSS signal for link (2, 0) in Figure 4.

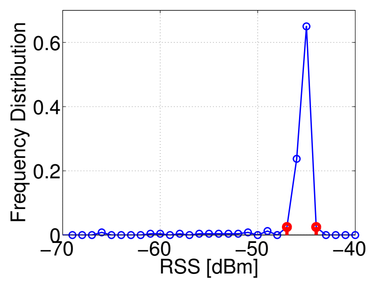

Figure 7. Frequency Distribution of the RSS samples within the time window considered in Figure 6. The distribution width, defined as the RSS interval wherein lie 90% of the samples, is highlighted.

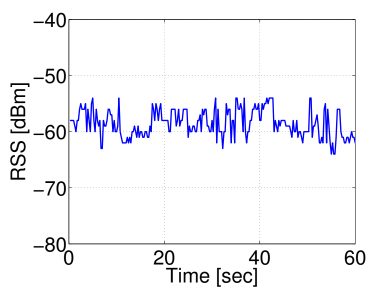

Figure 8. A one-minute slice of the RSS signal for link (1, 0) in Figure 5.

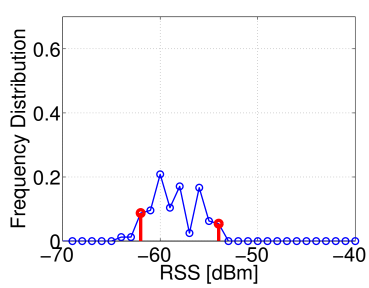

Figure 9. Frequency Distribution of the RSS samples within the time window considered in Figure 8. The distribution width is highlighted.

D. Counting People

Baseline Level Estimation: A simple method to gauge whether a given link is stable or not is for the node to keep track of the RSS Frequency Distribution (FD) over the sliding window (sliding FD). From a computational standpoint, this is a light task, because it only requires processing a number of RSS samples that is equal to the product of the number of samples per second and the window size. Because the duration of human-induced shadowing events is typically in the order of a few seconds (typically 1 to 4 seconds), we employ a sliding window of one minute. Because we use an IPI of 0.25 sec, the number of RSS samples to be processed is therefore equal to 60/0.25=240. The RSS baseline value can be simply inferred by looking at the Sliding Mode (SM), *i.e.*, the mode computed over a sliding window, which we found to be significantly more stable and therefore better suited to our purposes than EWMA filtering.

Stability Estimation: A quantitative measure of link stability can be obtained by looking at the width of the sliding FD (Sliding Width, or SW). We avoid the computation of the σ and simply measure the width of the RSS distribution as the size of the RSS interval wherein lie 90% of the collected samples. Figure 7 shows a one-minute slice of the RSS signal in Figure 4 (link (2, 0), a stable link), and Figure 6 shows the corresponding FD; the width is highlighted. Figure 9 shows a one-minute slice of the RSS signal in Figure 5 (link (1, 0), an unstable link), and Figure 6 shows the corresponding FD; the width is again highlighted, and it can be seen that it is significantly larger than its counterpart in Figure 8: a larger width corresponds to a more unstable link.

People Detection: Figure 10 shows an RSS trace of the duration of several minutes from link (2, 0) (the stable

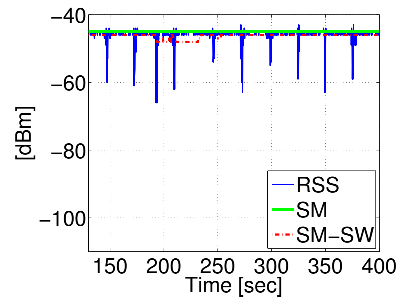

Figure 10. RSS, Sliding Mode (SM), and Sliding Width (SW) for link (2, 0), which is very stable: the SW is as little as 1.1dB.

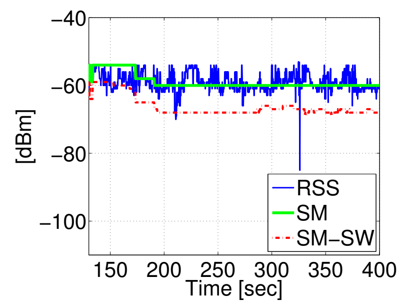

Figure 11. Link (1, 0) is fairly unstable: the average SW is as large as 5.9dB.

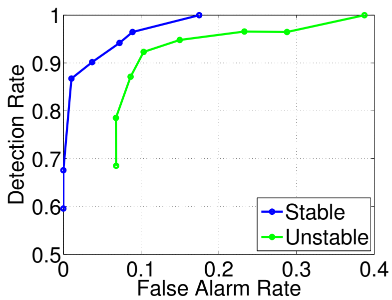

Figure 12. Receiver Operating Characteristic (ROC) curve for our online detection scheme measured at the deployment sites on a per-link basis.

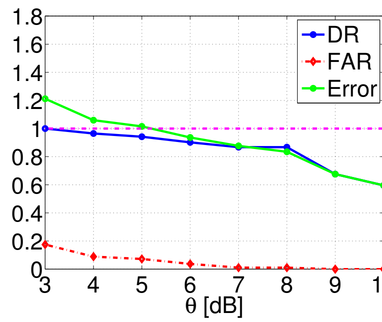

Figure 13. Detection Rate (DR), False Alarm Rate (FAR), and counting error as a function of the detection threshold θ for stable links.

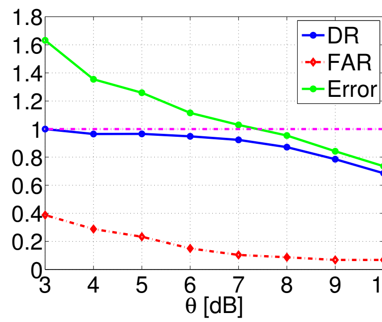

Figure 14. Detection Rate (DR), False Alarm Rate (FAR), and counting error as a function of the detection threshold θ for unstable links.

link featured in Figures 4 and 6), along with the SM and the SW (with respect to the SM); the average width of this trace is slightly above 1dB. Figure 11 shows an RSS trace from link (1, 0) (the unstable link featured in Figures 5 and 8), whose average width is nearly 6dB. We use our simple width estimation online to drive the deployment and to estimate the confidence of the count from a link. The count is incremented when the instantaneous RSS level drops below the SM by no less than a threshold θ, which we refer to as the detection parameter.

IV. Experimental Results

A. Deployment

We deployed two prototypes of our trail monitoring systems at two locations in Southern Switzerland proposed by the Ente Turistico Biasca e Riviera, an organization for the promotion of tourism in the mountainous area around the town of Biasca, about 20km north of the city of Bellinzona. We will refer to these two sites as the bridge site and the riverside site.

We ran an extensive experimental campaign to characterize the performance of our two prototypes as a function of the stability of the links (width) and the detection parameter θ. To study the effect of different width values, we have modified the relative positions of the nodes. In general, we found that a distance d (see Figure 2) comprised between 1m and 1.5m tends to result in very stable links with a width below 4dB, unless static fading is particulary unfavorable; we also found that the inter-transmitter distance r does not have a significant impact, and we chose it as dictated by the physical constraints of the deployment site. Our evaluation focuses on the traditional metrics studied in the context of detection theory: the Detection Rate (DR) and the False Alarm Rate (FAR), complemented by the counting error, defined as the ratio of the reported count to the ground truth. These parameters have been evaluated over several observations at each site and ground-truthed against manual counts. The system prototypes, powered by AA batteries, have remained on the field for one month.

B. Performance Evaluation

The curve for *stable* links only considers links with a width below 6dB, while links with a larger width are accounted for by the *unstable* curve. A clear performance dichotomy between stable and unstable links emerges from the Receiver Operating Characteristic (ROC) curve in Figure 12. This ROC curve was achieved by our detection scheme on a per-link basis on mote-class devices deployed at our two locations. This dichotomy is confirmed by Figures 13 and 14, which show the DR, FAR, and counting error as a function of the detection parameter θ for, respectively, stable and unstable links. These results clearly indicate the importance of an informed deployment: care must be exercised to ensure that the links between the deployed nodes are reasonably stable. Stability depends on the amount of multipath fading: the riverside site is located in a timbered area and is affected by heavier levels of multipath fading than the bridge site, while at the bridge site the measured width ranged between 1dB and 3dB, the measured width at the riverside site ranged between 3dB and 5dB. During the month-long operation, we have observed that stable outdoor links tend to remain stable over time, as we expected based on our indoor experience as well as the results in [16].

The ROC curve in Figure 12 also shows that it is possible to achieve a DR of about 0.9 with a reasonably small FAR.

Location	Width Interval [dB]	Detection Rate	False Alarm Rate	Per-Link Counting Error	Width-weighed Counting Error
Bridge	[1, 3]	0.94	0.07	1.04	0.93
River	[3, 5]	0.94	0.09	1.08	0.93

Table I
PERFORMANCE METRICS MEASURED AT THE DEPLOYMENT SITES

Figure 13 indicates that the detection parameter θ should be calibrated between 6 and 8 dB to achieve this performance level, but also shows that setting $\theta = 5$dB minimizes the counting error: with this calibration the FAR is higher, but so is the DR, and they partially compensate each other. Table I summarizes the performance obtained using $\theta = 7$dB. Treating all links as equal (excluding side-links), then the average count was 4% (8%) above the ground truth at the bridge site (river site). With a width-informed weighing (the narrower the width, the stronger the weight), we were able to eliminate the impact of the FAR and obtain an error slightly larger than 1-DR, resulting in an average count about 7% below the ground truth in both sites.

V. CONCLUSION

We have designed and built a prototype of a pervasive system for the radio-based counting of people on hiking trails. We used programmable mote-class devices to focus on the exploration of the rich parameter space of radio-based detection. We presented a rich set of results from a real-world deployment of our prototype networked system in two different locations. We showed that our scheme achieves a satisfactory counting performance with a low energy footprint, which could be further reduced through further optimizations (such as better time synchronization). Our system uses low-power wireless communication, which leaves it completely exposed to the vagaries of RF; for this reason, care must be exercised to ensure link stability at deployment time.

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