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COST EFFECTIVE SYSTEM FOR HUMAN PRESENCE DETECTION IN RURAL ENVIRONMENT

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Abstract

The present study investigates methods for detecting human presence in remote natural environments, including nature reserves and protected areas. Such regions play a critical role in environmental sustainability, and excessive human activity may adversely affect these sensitive ecosystems. Conversely, accurate estimation of visitor numbers is essential for effective management and long-term preservation of these areas. Several approaches exist for human detection, including optical systems based on visible-spectrum or infrared imaging. However, these techniques may raise concerns regarding privacy and personal data protection. To address these limitations, this research explores the application of Wi-Fi-based detection methods. Given that a significant proportion of mobile device users keep Wi-Fi functionality enabled, passive monitoring systems can identify and record Wi-Fi signal activity without direct personal identification. A dedicated hardware and software framework was developed to quantify mobile Wi-Fi activity within a designated remote study area. Validation was conducted by simultaneous visual counting, and the results indicate that Wi-Fi-based detection provides a reliable method for estimating the absolute number of visitors, as well as their temporal distribution.

Key words*: environment monitoring, data collection, sensor network, Wi-Fi.*

INTRODUCTION

Detecting human presence in nature has become increasingly vital for balancing conservation, education, and sustainable recreation. As more people seek connection with the outdoors, understanding where and when humans interact with wild spaces allows us to protect fragile ecosystems while highlighting nature's educational value. Nature trails, scenic overlooks, and biodiversity hotspots serve as living classrooms, demonstrating the importance of preserving habitats, biodiversity, and ecological processes. By monitoring visitation patterns - such as peak days of the week, time-of-day surges, seasonal trends, and rough visitor counts - land managers and educators can optimize trail maintenance, crowd-flow strategies, and interpretive programs that foster deeper public appreciation for the natural world (Leverington et al., 2010; Wu et al., 2015).

At the same time, certain sensitive areas must remain largely undisturbed to safeguard endangered species, prevent soil erosion, or maintain pristine habitats. Over-visitation in these zones can cause irreversible damage, from compacted trails and habitat fragmentation to the spread of invasive species carried on hikers' boots. Real-time or near-real-time detection of human presence enables authorities to identify emerging pressure points, issue timely alerts, or temporarily close sections before degradation accelerates. This dual approach - encouraging responsible access to "welcome" areas while quietly guarding "avoid" zones - helps ensure that nature's educational and recreational benefits endure for future generations (Lindgren et al., 2016).

The ubiquity of smartphones makes passive, cost-effective monitoring possible without invasive cameras or expensive sensor networks. Even when a phone's Wi-Fi is turned off, modern devices periodically broadcast 802.11 probe request frames in search of known networks. These tiny, anonymous radio signals can be captured by simple, low-power receivers placed discreetly along trails or at trailheads. By analysing the volume, timing, and movement patterns of these packets, researchers and park managers can estimate human presence and movement with surprising accuracy. This technique offers a privacy-

friendly, scalable solution that requires minimal infrastructure and can be deployed in remote locations where traditional counting methods (cameras, trail counters, or manual surveys) are impractical or cost-prohibitive (Wang et al., 2013; Farshad et al., 2014).

Ultimately, the goal is to present a practical, affordable methodology that transforms everyday smartphone emissions into actionable ecological intelligence. By turning the invisible digital chatter of visitors into meaningful insights about human-nature interactions, we can better protect wild places, enhance educational experiences, and promote truly sustainable outdoor recreation - all while keeping deployment costs low enough for widespread adoption by conservation organizations, national parks, and local communities.

MATERIALS AND METHODS

The test area

The Sóstó Natural Reserve is situated on the periphery of the city, in close proximity to the urban center. The area has a long-standing history of land use, having functioned as a recreational zone for approximately two centuries. Following the World War II, the site was repurposed as a municipal waste disposal area for nearly 40 years, during which both solid waste and sewage sludge were deposited.

Subsequent to the political transitions of the 1990s, extensive remediation and ecological restoration efforts were undertaken. As a result, the area was rehabilitated and officially designated as a protected natural reserve, ultimately becoming a prominent recreational destination for local residents. The hydrological conditions of the reserve are artificially supported: the wetland ecosystem is maintained through the daily input of approximately 550 m^3 of treated water supplied from a wastewater treatment facility (Udvardy et al., 2023).

The core of the reserve is located adjacent to the main sports arena of Székesfehérvár, reflecting a notable integration of urban infrastructure and environmental sustainability. The site attracts several hundred thousand visitors annually, and it also serves an important educational function, hosting structured environmental and sustainability programs in collaboration with local schools and the reserve's managing authority. Figure 1 shows the Sóstó natural reserve area with the city's contours as it locates very close to the city centre.



Figure 1. The Sóstó natural reserve test area

Human presence detection

Cameras, paired with computer vision algorithms (using edge AI or cloud-based processing), can identify humans based on shape, motion, or facial features. This approach provides the most accurate approximation of the number of people and can support additional attributes, such as age estimation. Cameras perform best in daylight conditions, although infrared (IR) cameras are available for low-light environments. However, machine-vision–based systems typically have high power consumption and significant cost. Their operation requires a clear line of sight, making them sensitive to occlusions and adverse weather conditions. Privacy concerns represent an additional and often critical limitation (Berger & Lu, 2022).

PIR (Passive Infrared) detectors sense differential infrared radiation emitted by warm, moving bodies as they pass through segmented Fresnel lenses. These sensors are highly attractive due to their ultra-low power consumption, cost-effectiveness, simple installation, and completely passive operation with no active emissions. However, PIR detectors have several inherent limitations (Andrews et al., 2020).

Their effective detection range is relatively short, typically between 5 and 12 meters, and they exhibit a high false-trigger rate caused by animals, direct sunlight, wind-blown vegetation, or environmental thermal gradients. In addition, PIR sensors are unable to count people, determine movement direction, or detect stationary humans. It is important to

emphasize that PIR sensors respond only to motion and provide a strictly binary output, offering no estimate of the number of people present (Gami, 2018).

Microwave Doppler sensors are compact radar modules, operating mostly at 5.8 GHz or 10.525 GHz, emit continuous-wave microwave signals and measure Doppler frequency shifts produced by moving objects. Their advantages include the ability to penetrate light foliage, clothing, or thin barriers, reliable operation in total darkness and adverse weather conditions such as fog, rain, or snow, a moderate detection range, and relatively low power consumption (Arab et al., 2022).

The main disadvantages are the inability to reliably distinguish humans from animals, swaying vegetation, or even moving water surfaces. These sensors are also sensitive to environmental vibrations and can detect only motion rather than static presence. In addition, regulatory restrictions on transmitted power apply in some countries, and the limited spatial resolution makes precise trail-segment counting or accurate crowd-size estimation challenging (Tada et al., 2022).

Ultrasonic transducers emit short acoustic pulses at approximately 40 kHz and measure the time of flight of echoes reflected from nearby objects. Their advantages include excellent short-range accuracy, very low cost, immunity to lighting conditions, and the ability to perform precise distance-based presence detection without relying on visual or thermal signatures. However, ultrasonic sensing has significant limitations in outdoor environments. The effective range is extremely limited in open natural settings, as sound waves attenuate rapidly and scatter due to wind and vegetation such as leaves. Performance is also highly sensitive to temperature, humidity, wind, rain, and ambient acoustic noise. Ultrasonic waves cannot penetrate vegetation or physical obstacles, and frequently produce false readings due to insects or small animals (Biryukova & Koretskaya, 2020).

Architecture

Wi-Fi communication is defined by the IEEE 802.11 standard. It is built entirely around the exchange of structured packets called frames.

Every transmission – whether announcing a network, requesting information, establishing a connection, or carrying actual data – takes one of three broad categories:

- Management frames are responsible for discovering access points, joining them, roaming between them, and maintaining the connection.
- Control frames manage medium access and acknowledge successful receptions.
- Data frames carry the actual user payload, mostly IP traffic.

The management frames are identified by the Type field in the Frame Control field being set to 00 (binary). The 4-bit Subtype field then specifies the exact kind of management frame. These frames handle network discovery, joining/leaving a Basic Service Set (BSS), authentication, association, and other administrative functions. Figure 2 shows the 802.11 packet structure which is the base for the system architecture (Du et al., 2025).

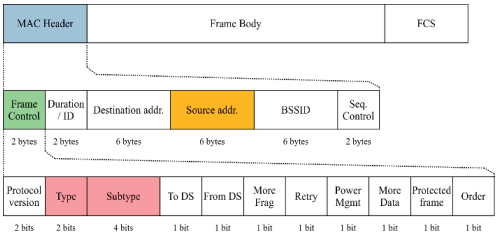


Figure 2. The 802.11 packet structure with the MAC header detailed

The defined management frame subtypes (as per the core 802.11 standard and its amendments up through recent revisions) are as follows, listed with their binary subtype values and common names:

- 0000 - Association Request;
- 0001 - Association Response;
- 0010 - Reassociation Request;
- 0011 - Reassociation Response;
- 0100 - Probe Request;
- 0101 - Probe Response;
- 0110 - Timing Advertisement (introduced in later amendments for synchronization);
- 1000 - Beacon;
- 1001 - Announcement Traffic Indication Message (ATIM) - used in Independent BSS (ad-hoc) networks for power-save coordination

- 1010 - Disassociation
- 1011 - Authentication
- 1100 - Deauthentication
- 1101 - Action (used for various management actions, spectrum management, radio measurement, etc.)
- 1110 - Action No ACK (a variant of Action frames that does not require acknowledgment, added in later amendments for efficiency in certain scenarios)

Subtypes 0111 and 1111 are typically reserved (unused or for future extensions), depending on the specific 802.11 amendment.

To connect to a Wi-Fi network, client devices such as smartphones and laptops must first discover which networks are available in their vicinity. One key method for this discovery is passive scanning, in which the device quietly listens across available channels without transmitting any frames. Access points (APs) in IEEE 802.11 wireless networks actively broadcast their Service Set Identifier (SSID) – the human-readable name of the Wi-Fi network – primarily through periodic beacon frames, which serve as the network's ongoing advertisement and synchronization signal.

These beacon frames are management frames transmitted at regular intervals, typically every 100-time units (approximately 102.4 milliseconds), on the AP's operating channel and at the lowest supported basic data rate to ensure maximum reachability by all potential clients in range. The SSID is included as a mandatory information element within the beacon frame body, allowing nearby devices performing passive scanning to discover available networks. This broadcast enables client devices to collect and list visible Wi-Fi networks (Gollier & Vanhoef, 2024).

Passive scanning requires a client device to listen on each Wi-Fi channel long enough to reliably capture at least one beacon frame from any nearby access point, since beacons are transmitted periodically – typically every 100-time units (approximately 102.4 ms), though the exact timing is asynchronous and unknown in advance. In the 2.4 GHz band, where most consumer devices operate in regions supporting channels 1 through 11 (or up to 13/14 depending on regulatory domain), this means the radio must remain powered on in receive mode for roughly 110-120 ms per channel to account for the beacon interval plus a small safety margin for channel switching overhead and potential beacon jitter. With 11 channels, a full passive scan can thus consume around 1.2-1.7 seconds of continuous operation of the radio, drawing significant power, often hundreds of milliwatts, during active listening. This energy cost is particularly burdensome for battery-powered smartphones. Figure 3 shows the in situ prototype of the detecting equipment.



Figure 3. Prototype of the Wi-Fi detection system deployed in situ

Another approach for network discovery is active scanning, in which client devices (such as smartphones and laptops) actively transmit probe request frames - management frames broadcast to the destination address ff:ff:ff:ff:ff:ff - targeting either specific known SSIDs (directed probes) or any available network (wildcard or null probes). This method is significantly faster than passive scanning because the device does not need to wait for the asynchronous arrival of beacon frames; instead, nearby access points that receive the probe request promptly reply with probe response frames containing the same essential BSS information (SSID, capabilities, security parameters, etc.) as beacons (Choi et al., 2017).

Hardware architecture

The hardware architecture of the human presence detection system is depicted in Figure 4. It is based on the ESP32-CAM module, originally designed to extend the ESP32 microcontroller with camera capabilities.

The board integrates a camera interface, an SD card slot, a Wi-Fi antenna, multiple IO ports, and a programming interface. In this implementation, the camera interface was not utilized. The ESP32-CAM was selected primarily because it offered the simplest design among available options that included a built-in SD card slot, while also being one of the most cost-effective solutions.

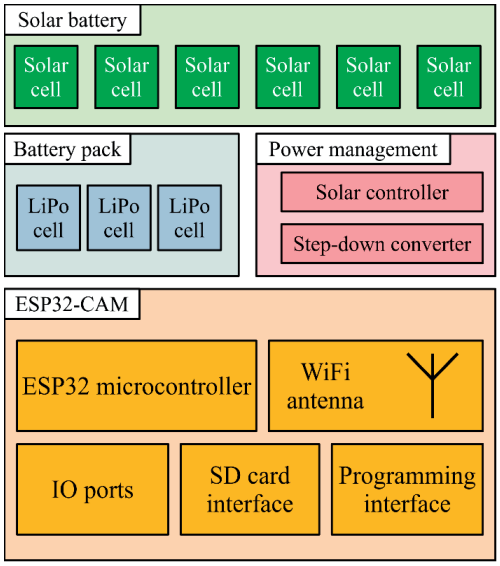


Figure 4. The hardware architecture of the system

The main component of the ESP32-CAM board is the ESP32 microcontroller. This device has two 32-bit xTensa CPU cores running at 240 MHz. The cores have IO port connections, high-speed serial buses (I2C and SPI) with DMA capability, timers and other common peripherals. The ESP32 stands out from the 32-bit ARM or RiscV families with its versatile Wi-Fi capabilities. It can act as a Wi-Fi client (station), access point (AP), or can even capture raw Wi-Fi packets.

The microcontroller is equipped with a 4 MB flash memory and 320 kB RAM to store the firmware and store the runtime data.

The ESP32 has several compatible sensor and other peripheral options from temperature, light, acceleration sensors to servos, SD card interfaces or even cameras.

The power source of the system is a 3-cell 2500 mAh lithium-polymer battery pack that provides a nominal voltage of 11.1 V. Power regulation and distribution are handled by a dedicated power management module, which incorporates both a solar charge controller and a step-down voltage regulator. Optionally, the battery pack can be recharged using a solar panel consisting of 6 photovoltaic cells connected in series.

Software architecture

The software of the human presence detection system is built on the FreeRTOS real-time operating system. FreeRTOS provides essential multitasking capabilities, including task management, scheduling, synchronization primitives, and message queues, along with direct access to the Wi-Fi subsystem and other hardware peripherals. Additional drivers handle SD card access and file system operations.

Upon boot, the Wi-Fi interface is configured in client (station) mode and attempts to connect to a predefined access point. Once connected, the system synchronizes its clock using the Network Time Protocol (NTP). Both the Wi-Fi connection and NTP synchronization are retried until successful. After time synchronization is completed, the Wi-Fi module is switched to a passive packet capture mode in which it listens continuously for all decodable packets, with probe request frames specifically filtered for processing.

Each captured probe request is placed into a message queue. Data from this queue is periodically flushed to the SD card as a CSV file at regular intervals (default: 30 minutes) or when the queue is nearing capacity. The CSV file is opened only during actual write operations and closed immediately afterward.

This approach, as opposed to writing after every packet or keeping the file continuously open, significantly extends the lifespan of the SD card and reduces the risk of file system corruption.

Each record in the CSV file contains the capture timestamp (year, month, day, hour, minute, and second), the source MAC address, the received signal strength (RSSI), and the

probed SSID. It should be noted that modern Android and iOS devices employ MAC address randomization and frequently transmit broadcast probe requests with an empty SSID field.
Consequently, a unique captured MAC address does not necessarily correspond to a unique physical device, and unique devices cannot be reliably distinguished based on the SSID field alone. Nevertheless, this method provides a practical and reasonably accurate approximation of the number of nearby Wi-Fi-enabled devices.

RESULTS AND DISCUSSIONS

To evaluate the performance and usefulness of the human presence detection system, the device was deployed at the Sóstó Natural Reserve in a remote area far from residential buildings and other human infrastructure. This placement ensured that the system would detect primarily visitors genuinely present in the protected natural area rather than nearby residents or passers-by.
Figure 5 presents the recorded data for a single day. The logged probe requests were aggregated into one-hour intervals, and for each hour the number of unique MAC addresses from which at least one probe request was received was counted.

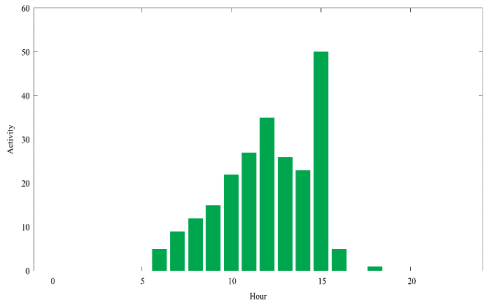


Figure 5. The collected and visualized activity data during a spring workday

As it was early spring, no visitors were detected before 6:00 a.m. or after 7:00 p.m. During the day, visitor activity showed a clear increase, reaching a first peak around noon. After a temporary decline, a second and larger peak occurred at 3:00 p.m., which corresponds to the most pleasant time of day for outdoor walks in early spring. A small additional peak was observed at 5:00 p.m., shortly after the typical end of a workday.
The absence of any detections during night time hours confirms that the system produced no false positives. The remote placement of the device, far from any residential areas, significantly contributed to this result by minimizing external interference.
This represents a notable advantage over many conventional human-presence monitoring systems, which often struggle with false triggers in populated environments. It is important to note that these detection-free periods were not caused by power loss, as any interruption in power supply is clearly visible in the system's log files.
The system's power consumption was also evaluated. After the initial setup phase, the average current draw stabilized at 39 mA. This low power requirement can be easily met by a moderately sized solar panel, even under modest lighting conditions. Furthermore, the system can operate autonomously for several days without solar input, with runtime depending primarily on battery capacity. For example, a compact 6 Ah battery can reliably power the system for approximately four days.
The robustness of the system was also evaluated through multiple power cycle tests. The log files remained fully consistent after each cycle, with no data loss or corruption observed.

CONCLUSIONS

The Wi-Fi-based sensing systems represent a robust, scalable, and privacy-aware solution for monitoring human presence in remote natural environments, such as protected areas and nature reserves. Unlike conventional optical or infrared-based detection systems, which may raise significant concerns regarding personal data protection and require favourable environmental conditions, the proposed approach leverages passive monitoring of Wi-Fi probe signals. This enables an indirect yet effective detection of human presence without capturing personally identifiable information, thus aligning well with increasing legal expectations related to privacy.
The newly constructed hardware and software framework demonstrated reliable performance

in a real-world scenario. The system was capable of continuously capturing Wi-Fi signal activity and transforming it into meaningful indicators of visitor presence and movement patterns.

Comparative validation using simultaneous visual counting showed a strong correspondence between measured Wi-Fi activity and the actual number of individuals present in the monitored area. In addition to estimating absolute visitor counts, the system also provided valuable insights into temporal dynamics, such as peak visitation periods and fluctuations in human activity over time.

These capabilities are particularly relevant for environmental management and conservation practices. Accurate, continuous, and non-intrusive monitoring can support decision-makers in assessing anthropogenic pressure on sensitive ecosystems, optimizing the number of visitors and implementing adaptive management strategies. Furthermore, the relatively low cost, ease of deployment, and minimal maintenance requirements of Wi-Fi-based systems make the system especially suitable for large-scale or hard-to-access regions where traditional monitoring infrastructure may be impractical. Solar powered solutions contribute to solve sustainability challenges.

Despite the many advantages there are certain limitations that must be considered. The method inherently depends on the proportion of visitors carrying Wi-Fi-enabled devices with active signal broadcasting, which may introduce bias in absolute estimations under specific demographic or behavioural conditions. Additionally, environmental factors such as terrain, vegetation density, and signal interference can influence detection range and accuracy. Addressing these challenges may require calibration procedures, site-specific parameter tuning, or the integration of complementary sensing modalities.

Future research directions include the fusion of Wi-Fi sensing with other non-invasive technologies such as another environmental sensor, the application of advanced data analytics and machine learning techniques for improved signal interpretation, and the development of adaptive algorithms capable of compensating for environmental variability. Expanding long-term deployments across diverse ecological contexts would further validate the generalizability and reliability of the approach.

In summary, the presented Wi-Fi-based detection methodology offers a promising pathway toward sustainable, privacy-conscious and data-driven monitoring of human activity in ecologically sensitive areas, contributing to more effective conservation and management practices.

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