The Evolution of Wi-Fi Technology in Human Motion Recognition: Concepts, Techniques and Future Works

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Abstract. Human motion recognition is an important topic in computer vision as well as security. It is used in scientific research, surveillance cameras industry and robotics technology as well. The human interaction with the objects creates a complex stance. Multiple artefacts such as clutter, occlusions, and backdrop diversity contribute to the complexity of this technology. Wi-Fi signals with the usage of their features could help solve some of these issues, with the help of other wearable sensors, such as: RGB-D camera, IR sensor (thermal camera), inertial sensor etc. This paper reviews various approaches for Wi-Fi human motion recognition systems, their analytical methodologies, challenges and proposed techniques along with the aspects to this paper: (a) applications; (b) single and multi-modality sensing; (c) Wi-Fi-based techniques; d) challenges and future works. More research related to Wi-Fi human related activity recognition can be encouraged and improved.

Keywords. *Human Motion Recognition, Wi-Fi, Sensors, Computer vision, Cybersecurity*

1- INTRODUCTION

Human motion recognition has been recently been an important topic in many fields, including computer vision, computer networks, cyber security, surveillance-based industry and ubiquitous assistive living [1]. HAR seeks to comprehend people's daily habits by observing them and their surroundings. Sensors in cellphones, wearables, and home settings capture this data. Computer vision uses a digital and video-based systems to collect daily human actions and identify them automatically [2]. With the evolution of digital logic and computer systems, low-power, high-capacity, low-cost sensors, as well as wireless networking networks, have become increasingly common. This is the main reason individuals use technology and technologies for daily subsistence. The activity recognition mechanism can be used to track daily exercise [3].

Identifying static and dynamic tasks with postural shifts can also help monitor worker health and productivity. These systems can also help people maintain a healthy lifestyle by advising little changes in their behavior. Soldiers in strategic circumstances require precise information on their activities, health, and locations [4]. This data can be quite useful in combat and practice settings. Smart houses use external sensing to track daily tasks. The use of cameras for surveillance and interactive reasons is appropriate. These systems use motion history photos and computer vision to distinguish action [5].

Human activity recognition is important in human-to-human interactions. It is tough to extract since it contains information about a person's identity, personality, and mental state. The ability of humans to detect other people's actions is a major research topic in machine learning and artificial intelligence

[6]. As an outcome of the study, numerous applications such as video surveillance, HCI, and human behavior modelling demand a multiple action identification system. In order for a computer to identify human activities efficiently, the person's kinetic states must be determined. Human behaviors like “walking” and “running” come effortlessly and are easily recognized. Complex tasks. Complex tasks can be broken down into simpler ones that are easier to recognize [7].

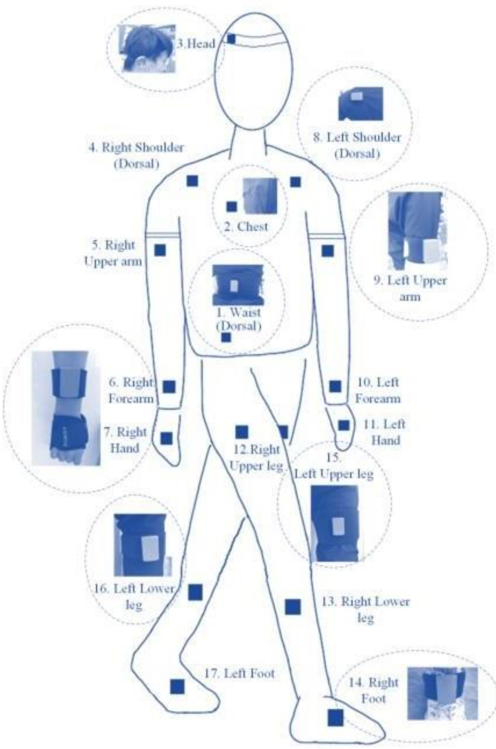

Fig 1.: Examples for wearable sensors with human body for motion detection

Object detection in a scenario can help understand human activities and provide relevant information about the current occurrence. Problems including backdrop clutter, partial occlusion, length, perspective, sunlight, and look make it difficult to identify human activities in video or still photographs. Many applications, such as video surveillance, HCI, and human behavior modelling, require multiple activity recognition [8]. We cover recent and current research advancements of human activity identification. We categorize human activity approaches and examine their benefits and drawbacks as well as categorizing human activity classification approaches into two broad categories based on whether they employ data from several modalities. This is followed by sub-categories that represent how they simulate human behavior and their interests.

Many researchers from various fields have sought to comprehend human mobility. The issue is unique to each discipline. With so many reasons for researchers, many methods have been introduced across fields. These contributions provide a better knowledge of human mobility. However, this article focuses on the computer vision part of human motion understanding, namely entire body movement [9]. This article attempts to recall some of the most quoted and recent evaluations over the last two decades, while highlighting the subject's relevance and wide-ranging applications. The large range of challenging and promising applications for human motion analysis, recognition, and understanding has sparked significant research in computer vision. Following is a survey of multiple applications in several domains:

■ **Smart Surveillance:** Due to the boring and hypnotizing nature of monitoring video scenes, and the increasing number of cameras covering vast areas, the human operator becomes more costly and unreliable (Such as:, a survey of CCTV (Closed Circuit Television) systems). So the demand for automated surveillance systems becomes urgent. Smart surveillance can be used to detect suspicious behavior and unusual events, understand and describe human behavior in dynamic situations (Such as:, monitoring activities over a large area using a distributed network of active video sensors), and control access to sensitive areas like military bases and government offices [10].

■ **Behavioral Biometrics:** Recognition of individuals using behavioral signals (Such as: stride, length, facial features) does not require subject participation or involvement [11].

■ **Human-Computer Interaction:** Examples of perception user interfaces include gesture-driven control, eye gaze monitoring, voice recognition, sign language processing and understanding, signaling in noisy environments such as factories and airports, and cognitive user interfaces which enables people to interact with computers without using a keyboard or mouse [12].

■ **Virtual Reality:** in which an allows the user to interact with a virtual computer systems environment, such military training or fireman and rescue team training. Games and entertainment sectors have various uses for virtual reality [13].

■ **Smart Environments:** Extracting and keeping awareness of a broad range of activities and human behaviors, Such as:, monitoring conference room exchanges [14].

■ **Games Industry:** Several games feature gesture-based interactive technology, which uses motion capture to allow non-intrusive body movement involvement. Like the popular Microsoft Kinect Xbox [15].

■ **Entertainment Industry:** Motion-captured characters replace actors in science fiction films (digital avatars) [16].

■ **Sports Motion Analysis:** such as soccer, where referee decisions and tactics are analyzed, as well as automatic highlight identification and video annotation and browsing [17].

■ **Robotics Learning to Copy Human Behavior:** utilizing robots to set up or clean tables, or in dangerous scenarios or surroundings like vehicle crash tests, skating during an arctic blast, etc. [18].

■ **Smart Driver Support Systems:** Such as: Monitoring Driver Consciousness, Sleep Identification, Airbag Network Management, Anticipating Driver Turn purpose ,etc. [19].

In order to achieve human motion analysis and recognition, these applications demand varying levels of performance (Such as: human modelling, real-time processing, video resolution) and environmental control (Such as: regulated or uncontrolled) [20]. These applications' requirements for body motion recognition and classification differ (Such as:, human modelling, real-time analysis, video resolution, controlled or uncontrolled environments, active or passive sensing, types and number of sensors, performance robustness and accuracy) [21].

1.1 Background

A wireless signal rebounds off walls, objects, as well as other surfaces. The innovative idea is used to save hostages in a difficult and dynamic situation. Indoor location uses fine-grained Wi-Fi signal information to find people based on path-loss characteristics [22]. Activities are recognized by limiting the interference from individuals or changes in the environment. Motion detection and estimation are attractive and demanding research topics. Applications that use Wi-Fi signals face new problems and opportunities. Indoor location tracking can benefit from mobility information. But it can make signal processing more challenging. Recent research uses Wi-Fi signal changes reflected by motion to identify human movement [23]. Motion has two properties: speed and orientation. Some works focus on resolving motion. In a dynamic setting, fast motion promotes Wi-Fi signal change rate. Motion tracking has grown rapidly in recent years.

Human movement evaluation and identification has many surveys, each with a distinct purpose and taxonomy to compare different publications. Earlier research in human movement is classified as model-based or non-model-based. whether explicit or implicit Model, Modeling human movements, Body parts used in motion analysis, Full-body or body part motion, Detail required to comprehend human behaviors and spatial dimensions [24]. Sensory mode , Sensory diversity, Location and mobility, Whether active or passive, Marker-based or not, Tracking one or more people, Assumptions about motion , Usability, Image representation, Segmenting video.

1.2 Challenges

This study analyses motion detection algorithms and evaluates motion impact on Wi-Fi based applications. Overall, estimating the impact of motion behavior poses the following issues. This problem stems from two aspects: target proximity to non-target and device-free motion detection.

• ***Create a framework for estimating motion behavior*.**

Work already done on dealing with unusual motion behavior in experiments cannot be applied to a new context.

• ***Estimate the link between motion and Wi-Fi signal variations in a random interior environment.***

As a result of this relationship, it is possible to determine the performance of data sets from various experimental situations. The recognition difficulties in the domain of sensor-based motion identification can indeed be examined. The difficulty of the activities varies depending on their quantity, kind, sensor selection, power usage, obtrusiveness, and information gathering procedures.

As illustrated in the figure 2 below, ambulation activities are grouped as static, dynamic, either with postural changes. It is easier to identify static actions (sleeping, sitting, etc.) than monitoring compliance (running, training, etc.). Due to significant overlap in feature space, extremely comparable poses (sleeping, standing, etc.) cause tremendous complexity in separation. Additionally, dynamic activities (going upstairs and downwards) are difficult to distinguish due to comparable movement patterns.

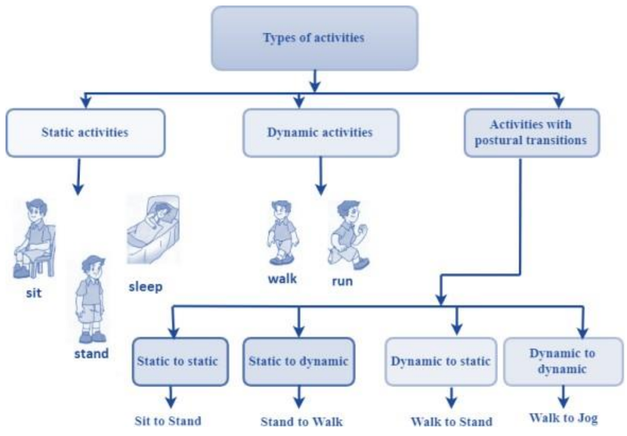

Fig. 2. The classification different common activities techniques for human.

In most situations, the correlation between completed tasks is inconsistent during the duration of the activity, making identification even more difficult. For example, whereas sitting and standing are closely linked, they are quite distinct from walking. Transitional activities may be classified into four categories [25]:

1- Static to Static Postural Transitions.
2- Static to Dynamic Postural Transitions
3-Dynamic to Static Postural Transitions.
4-Dynamic to Dynamic Postural Transitions.

a- **Sensors:** The amount of sensors, kind of sensors, and position of the handset while collecting information from people can greatly enhance the sophistication of the identification algorithm [26].

b-**Chosen Sensors Numbers:** In addition to the usual Wi-Fi and Bluetooth sensors on a mobile are sensors for temperature and relative humidity as well as light conditions and proximity. However, an identification system with a limited number of sensors makes the procedure quicker and easier in real-life applications. The quantity of wearable sensors is crucial for convenience. Users cannot carry several sensors. The balance between sensor count and efficiency should be handled with attention [27].

c- **Wearable Sensors Location:** Typically, people carry their cellphones in the coat pocket, trouser wallet, or hand. Because trackers detect motion along an axis and the accelerometer identifies direction, the posture of the device must be evaluated when gathering information, as data might vary depending on the sensor placement on a person's body, even within the same activity. However, owing to the placement of phones and wireless sensors, incorrect detection of a certain activity might impair recognition rate. Further issue is that some users may forget the device at home, making it hard to follow their behavior. In this situation, a wearable sensor may be a viable alternative, however several consumers may find it uncomfortable to keep it every day while doing tasks [28].

The paper is organized as following:

Section

2. WIFI SIGNALS AND MOTION TYPES

2.1 Wi-Fi Signals

Path loss, middle-scale shadowing, with narrow multi-path fading could all be used to mimic wireless transmission in a complicated environment. Earlier investigations focused on receiving signal strength (RSS), easily obtained in wireless environments. It's only that RSS is prone to multi-path effects. Then, instead of RSS, some works use channel state information (CSI). It proposes super-resolution methods that reliably compute multi-path component AoAs with a median precision of 40cm. A 65cm precision Chronos could calculate sub-nanosecond moment using cheap Wi-Fi devices. Table 1 shows Wi-Fi signal properties exploited in various Wi-Fi applications.

Table 1: Most used Wi-Fi Signals Approaches with their properties

Approach	*Properties*
AoA	A well-known approach for analyzing multiple activities in a project, particularly the time necessary to accomplish each activity.
RSS	Average, Range, and Signal Variance
ToF	The time delay between the signal ransmission and its arrival to the sensor after becoming returned by an element.
CSI	Intensity, Phase, Variance, Complexity of Signals, Change in Signal Speed and Correlation Value

2.2 Motion Patterns Types

Figure 3 below divides motion patterns into three types. First, target motions have a massive effect on Wi-Fi signals in everyday life. Second, non-target motions modify Wi-Fi signals, affecting the motion target detection accuracy.

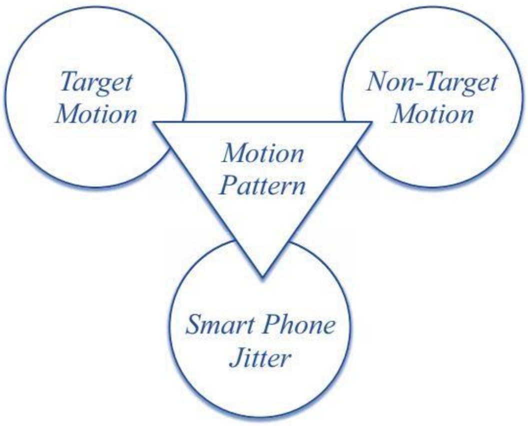

Fig.3.: The intersection between Motion Pattern along with Target/non-target Motion along with Smart Phones.

It is the main obstacle for current Wi-Fi-based applications. Finally, wireless device latency effects motion pattern.

a- Target Motion:

Target motion depicts an object's activity in an indoor setting. The target's motion and direction are crucial factors in assessing the influence of motion on Wi-Fi transmissions. A moving target can alter the range between the object and the transmitter, enhancing the multi-path impact. Wi-Fi signal effects caused by object movements can anticipate target traces and behavior [29].

b- Non-target Motion:

Non-target objects are persons who do not engage in the experiment but effect Wi-Fi transmissions. Non-target activities modify Wi-Fi signals faster than static targets. In this case, distinguishing non-target activities with static objects is critical for Wi-Fi based applications. DeMan uses chest motion signal model to identify object activity from non-target activity [30].

c- Wireless Device Jitter:

In mobile situations, it is difficult to maintain constant state. The target's arm movement causes a slight shift in Wi-Fi signals. If it simply uses Wi-Fi signals, it's hard to tell the difference. As example, word recognition algorithms establish a relationship model among keywords and Wi-Fi signal variations represented by keyboards by imposing environmental constraints [31].

3. TECHNIQUES AND PERFORMANCE

3.1 Techniques

3.1.1 Signal processing of Wi-Fi sensing

Signal processing for Wi-Fi sensing includes noise reduction, signal transformation, and signal extraction [32].

3.1.1.1 Noise Reduction

Raw CSI data contains noise and outliers that might degrade Wi-Fi sensing capability [33].

3.1.1.2 Phase Off-sets Removal

Raw CSI readings in Wi-Fi systems include phase offsets owing to equipment / software issues. The Sampling Time Offsets (STO) occur when the receiver and transmitter's sampling clocks/frequencies are not synced. Some identification and classification algorithm aren't phase sensitive. Get CSI changing patterns. Use CSI phase discrepancies of neighboring time samples or sub channels. It cancels CSI phases offsets assuming they are constant across packages and carrier frequency. However, it can recover phase transition patterns for use in classification algorithms [34]. Many estimate tasks demand precise phase shifts. AoA and ToF estimation mistakes caused by phase offsets are utilized to track and locate people and objects. SpotFi reduces STO/SFO by regression analysis, however ignores CSD- induced phase changes between transmit antennas. Multiple linear regression is introduced in SignFi [35].

$$\Theta_{i,j,k} = \Phi_{i,j,k} + 2\pi f_\delta k \left(\tau_i + \rho + \eta \left(f_k'/f_k - 1\right)\right) + 2\pi\zeta_{i,j},$$

$\Phi_{i,j,k}$ represents the CSI phase, which is brought upon by multi-path effects.

τ_i, ρ, η, and $\zeta_{i,j}$ represent, correspondingly, the phase offsets generated by CSD, STO, SFO, as well as beam-forming.

f_{δ}: is the difference in frequency between two successive subcarriers. Phase offsets are estimated, by minimizing fitting errors over:

K, represents Subcarriers

N, represents Antennas Transmission

M, represents Antennas receivers

$$\widehat{\tau},\ \widehat{\omega},\ \widehat{\beta} = \arg\min_{\tau,\omega,\beta} \sum\nolimits_{i,j,k} \left(\Theta_{i,j,k} + 2\pi f_\delta k\,(i\tau + \omega) + \beta\right)^2,$$

Eliminating phase offsets enhances productivity for single- and multi classification purpose as well. It reconstructs CSI step patterns above a range of sub-carriers and recording time intervals. Raw CSI phase measurements provide redundant data on how CSI stages vary. Unwrapping CSI phases and recovering lost data is accomplished by removing phase offsets [39].

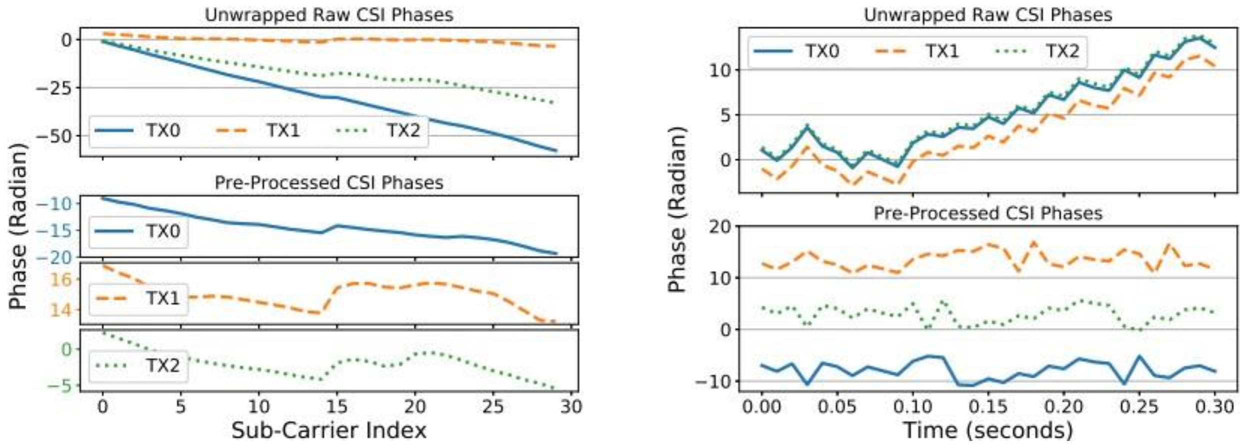

Fig. 4: Raw CSI observations might not represent the mechanism CSI processes; as it vary with both time and sub-channels

As seen in figure 4 above, unprocessed CSI stages vary regularly between and, but pre-processed CSI stages vary almost linearly throughout a broader range. Additionally, time-dependent CSI phase variations are rectified. As seen in the figure above, the raw CSI stages of the first and second frequency channels vary identically, but their shapes after pre-processing are indeed different [36].

3.1.1.3 Outliers Removal

Moving Average and Median Filters are both straightforward and commonly used techniques for filtering out high frequency noise [37]. Every data point is changed by the median of the datasets immediately adjacent to it. Typically, a sliding window and multiplication factors are employed to generate various weights, for examples:

- Weighted Moving Average (WMA)
- Exponentially Weighted Moving Average (EWMA).
- Low Pass Filters (LPF)

They can also be used to eliminate high frequency noise when signal transform techniques such as the Discrete Fourier Transform are used (FFT). Wavelet Filters are identical to LPFs; the primary distinction is that they employ the Discrete Wavelet Transform (DWT) rather than the Fourier Transform (FFT) [38].

Where:

$\mathbf{m_i}$ represent the median,

$\boldsymbol{\sigma_i}$ represents Standard Deviation

The Hampel Filter calculates the mean score and standard deviation of such a region of closely spaced data points [40]. If it exceeds a certain threshold, the existing point is considered an outlier and is substituted with the median. Occasionally, outliers are eliminated instead of being substituted by medians.

The Local Outlier Factor (LOF) is a frequently used technique for detecting anomalies [41]. It quantifies a data point's local density in relation to its neighbors. The local density is determined by the Wi-Fi tethering distance between two points. Outliers are number of observations with a considerably lower density distribution than their neighbors. Signal Nulling is a specialized approach for removing outliers from Wi-Fi sensing. Wi-Fi devices may employ both hardware, such as antenna arrays, and software, such as transmit beam shaping and noise cancellation algorithms [42].

3.2 Signal Transformation

Time-frequency analysis of CSI readings uses signal transform techniques. In this perspective, the signal convert output shows CSI change pattern frequency instead of carrier frequency [43]. Table 2 below summarizes signal conversion techniques.

Table 2: Approaches for Wi-Fi Sensing Signal Transformation

Technique	Equation
Fast Fourier	$X[k] = \sum_{n=1}^{N} x[n]e^{-j2\pi kn/N}; k$
Discrete Wavelet	$y_{1,high}[n] = \downarrow Q[\sum_{k=-\infty}^{\infty} x[k]h[n-k]]; \downarrow Q[\cdot]:$
Short Time Fourier	$X(t,k) = \sum_{n=-\infty}^{\infty} x[n]w[n-t]e^{-jkn}; t:$
Discrete Hilbert	$y_{1,low}[n] = \downarrow Q[\sum_{k=-\infty}^{\infty} x[k]g[n-k]]$

With an LPF, FFT can eliminate high frequency sounds. It can also acquire target signals with Band Pass Filters (BPF). Examples of this include when a person is stationary or moving nearby. The Short-Time Fourier Transform (STFT) splits the input into equal-length segments and computes the FFT coefficients independently for each segment, as shown in the table above [44]. By displaying data from both time and frequency, STFT may detect changes in dominating frequencies over time. As seen in the Table above, DHT adds a /2 phase shift to the lower frequency range of FFT. It transforms a time series of legitimate data into a complicated helical sequence. DHT can analyze the immediate characteristics of a CSI measurement series. STFT does not ensure good frequency and temporal resolution [45].

Time resolution is improved with a large window length. The frequency components are easily identifiable, but not the frequency variations. A limited window length enables for detection of signal changes but not exact frequency identification. The Wavelet Transform provides good time and frequency accuracy for low-frequency signals. The DWT output can be wavelet-filtered to eliminate noise. DWT is much more robust then Doppler phase shift in preserving mobility data [46].

3.3 Signal Extraction

Signal extraction is used to extract goal frequencies from CSI data. Unidentified or repetitive signals may need thresholding, filtration, or signal encoding [47]. To acquire additional information, various signal sources are combined and data is interpolated. These approaches are shown in the table below.

Probability Model:

The acquired data is used to train a probability model. Nevertheless, probability model-based methods are not universal. Horus displays model invalidation whenever the environment changes. We illustrate two flaws in probability-based techniques [48].

Time-dependent environment: The same device gathers information from a certain environment at various times. Also, the probability pattern of every training differs somewhat, causing a huge inaccuracy to applications reliant on Wi-Fi signals [49].

Instability: The probability theory depends on the training dataset and training methodology. The probability model may modify if the training set or training technique changes [50].

3.4 Fingerprint-based:

The fingerprint-based solution incorporates two phases: gathering RSS from each place inside a building and matching it with the fingerprint database. These works can achieve meter-level precision without a site survey [51]. High implementation costs and lack of adaptability to changing environments limit its usefulness. We illustrate three flaws in fingerprinting approaches [52].

Expensive: Building a fingerprint database requires a lot of labor and hardware. The more location data collected, the more accurate indoor location becomes. A fingerprint database must be updated in real-time when the indoor environment changes. This constraint increases system burden in practice [53].

Best Location Choice: Various works choose some places of interior maps to save money and preserve high accuracy. That is, only a few places may depict indoor maps coarsely [54].

The difficulty is to select several areas to accurately portray indoor maps.

Crowdsourcing Model

Crowdsourcing-based systems collect data from a large number of mobile devices located across an indoor space, saving time and money. However, as illustrated below, actual crowdsourcing applications face some problems [55].

Device Diversity: Device diversity is a problem in wireless environments. Wi-Fi transmissions are sensitive to both indoor and outdoor environments, as well as device kinds. The impact of device diversity on data collection is often overlooked [56].

Destabilization of Data Source: Smart phones used in crowdsourcing are unknown and cannot ensure data authenticity [57].

Time Synchronization: Due to the nature of Wi-Fi transmissions, crowdsourcing requires time synchronization of the devices collecting data. Nevertheless, numerous mobile devices do not have synchronization capabilities [58].

Performance: Existing works aim for higher performance at affordable cost. The effectiveness of existing approaches is shown below.

Accuracy: Because RSS is easily accessed by commodity Wi-Fi infrastructure, existing works still use RSS information to identify motion. These devices use Wi-Fi signals and human movement to attain excellent accuracy.

a. WiSee uses doppler shifts in radio waves to detect human activity with 97 percent accuracy and E-eyes with 92 percent.
b. Smokey uses CSI to recognize smoking activities in NLOS and through-wall situations.
c. The system uses foreground detection to retrieve useful information from numerous noisy sub-carriers, even when posture changes.

2) Cost: Earlier, experts believed that the more APs deployed, the better the accuracy. APs are typically used in early works to achieve precision. Horus has an average inaccuracy of 0.6m by 4-6 APs. In recent years, single APs like Chronos, with a median inaccuracy of 65cm, have achieved the same degree of precision as multi-Aps [59].

3) Robustness: In a dynamic indoor environment, resiliency is a significant measure of system quality. Several works offer methods with great LOS precision but poor NLOS accuracy [60].

These days researches can supply different methods. Smokey [61] can detect smoking in LOS, NLOS, and through walls.

4. MOTION INFLUENCE

4.1 Advantage

Previous works were made to avoid motion because it affects the changing of Wi-Fi signals. We studied mobility detection strategies and their influence in recent years. Three points are summarized below.

1) Enrich Multi-Path Data: The interior setting, multi-path effect is common. Indoors, there are usually 6-8 paths. Understanding people circulation patterns can assist discover energy hotspots and corridors that can help commercial site selection. Human mobility can reset an indoor environment's floor plan, and multi-paths respond. Li-Fi detects LOS by skewed CSI distribution. PhaseU also completes real-time LOS identification indoors. Others use multi-paths to achieve internal localization or human motion detection. [62].

2) Lowering Device Cost: Wi-Fi offered a moving target to replicate the antenna array (Fig. It can lower device costs and improve applications including indoor localization, people tracking, and access management. A moving target is focused on by using MIMO disturbance nulling to reduce static object reflections. We can consider people in a closed space if they don't move [63].

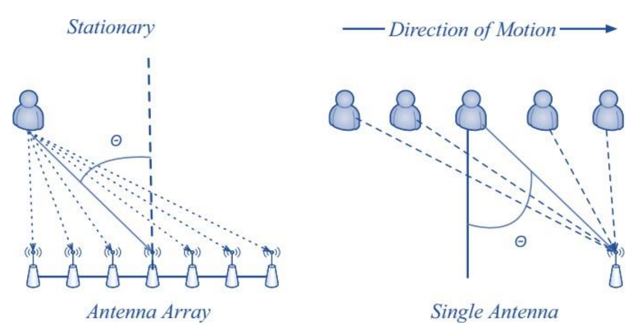

Fig.5.: The detection of moving objects through Single Antenna and Antenna Array

3) Reducing the Requirement of Indoor Environment: The indoor environment affects wireless transmissions. Wi-Fi signal signatures do change with time and environment. However, this feature complicates Wi-Fi based applications. Indoor fingerprinting is not feasible since the signature varies with the environment. Authors often seek to suggest an ubiquitous plan for dealing with dynamic tests [60].

Table 3: Common proposed approaches along with highest accuracy results

Proposed Methods	Approach	Accuracy
ArrayTrack [61]	AoA	35cm
SAIL [62]	ToF	2.2m
SpotFi [63]	AoA	39cm
CUPID [64]	Human Mobility	4.2m and 1.5-4 APs: 3.6m
Chronos [65]	ToF	63cm & NLOS: 96cm

4.2 Disadvantage

1) **Infected Wi-Fi signal datasets**: In general, Wi-Fi signal data packages allow RSS and CSI acquired by receivers indoors. Motion has a greater impact on Wi-Fi signals compared static. We gather dataset, measurements, and other background data. Without particular approaches, it is hard to identify targets' data from collected data sets. Researchers offer a few approaches to resolve other noisy data [66].

2) **Difficult Pre-processing:** Due to the complexity of motion characteristics, the preprocess phase becomes more difficult. Static behaviors modify Wi-Fi signals slightly, but motion behaviors produce considerable changes. Meanwhile, gathering data from the receiver is difficult to identify outlier from motion behavior [67].

3) **Hardware Consumption Increment:** Motion lowers the stability of mobile device data sets and the effectiveness of Wi-Fi based technologies. It acquires more APs (5-6) as well as other detectors for great accuracy. Currently, some studies integrate Signal strength with sensor information to obtain the same purpose as Wi-Fi signals alone.

5- DISCUSSION

In this part, we compare prior classification techniques for several of the baseline methods. Using a waist-mounted accelerator, they devised a method for collecting data from 6 participants on 12 everyday tasks. This paper presented a way to maximize signal processing within the wearable unit's PCB [68]. Their concept uses embedded cognition and actual categorization systems. Their total accuracy was 90.8 percent, while postural orientation identification was 94.1 percent and potential fall detection was 95.6 percent.

In contrast, the study [69] proposes 1D Haar-like filtering approaches, which are not only novel feature extraction techniques but also need less computing. Their technique improved recognition accuracy by 93.91 percent while lowering computation costs by 21.22 percent.

To make features more robust, [70] used both (1- Kernel Component Analysis & 2- Linear Discriminant Analysis) following extraction. Finally, they utilized a DBN to train the features. They found 89.61 percent accuracy, beating out multi-class SVM (82.02 percent) and Artificial Neural Networks (65.31 percent).

In recent years, deep learning and generic classification algorithms have been used to recognize sensor-based activity. Semi-supervised ML based motion detection approach for a little quantity of labelled training data to solve the problem of incorrect labelling. [71] utilized an unsupervised machine learning approach based on KMeans clustering to detect human activity. However, these approaches perform poorly when the datasets contain both static and dynamic activity. While [72] began fresh research on estimating a user's path using sensor data. This could enhance context-aware services, and location-aware services, they claim. In order to enhance mobile detection and recognition with erroneous time stamps, [73] in their research used EM+Sparse and EM+Dense techniques for the HASC and UCI HAR datasets.

Using a deep recurrent neural network, Inoue et al. [74] presented a technique with high throughput using raw accelerator data. other simplistic techniques. The Multi-Class

Hardware-friendly SVM Classifier technique employs fixed-point arithmetic for the classification of actions rather than the conventional. In their research [75] introduced the Mod method using Random Forest classifiers to classifying mobility and distribution and transportation. A weighted mixture of multiple classifiers is utilized in earlier work [76] to recognize activity data from body sensors.

6. FUTURE WORKS

Future study should analyze resource use, including memory, CPU, sensor count, and most significantly, battery usage. The most prevalent trade-off between identification accuracy, precision, and resource use should be investigated further. A collection of classifiers could be used to correctly identify comparable behaviors like sitting and standing, walking upstairs and downstairs. Most current efforts have failed to differentiate comparable actions precisely using one classifier. Future plans should also include working with incorrectly classified manual training data, including walking activity being mislabeled as running owing to human error. Video data fusion with sensor data is an important topic to investigate.

Using machine learning algorithms, fine-grained Wi-Fi signal information accurately represents micro-mobility behavior, perceives the environment, and anticipates unknown behavior. Several research groups focus on device-free motion detection utilizing Wi-Fi signals.

■ **Human Detection:** Researchers are focusing on noninvasive human detection. Noninvasive means no attachment required, and passive participant in detection. Non-invasive applications can increase people's freedom (convenience) and lower hardware costs. For now, it poses severe obstacles such as reliance on environment and good quality data.

■ **Identifying Motions:** The wireless channel between both the application and the AP is supposed to change. The fine-grained multi-path topology may vary as the surroundings or device shifts. RSS cannot capture small variations in the wireless channel since it collects an average indicator of all multi-path variables. So, in the complexity environment, we use CSI or AoA to identify between motions.

■ **Tracking User Activity:** Monitoring user behavior uses Wi-Fi signals to monitor human behavior and forecast unknown behavior. Wi-Fi connections can track shoppers at the entryway. We use fine-grained Wi-Fi signal information to follow and evaluate human behavior.

7. CONCLUSION

Activity identification is the next wave of context-aware customized applications in several developing computer domains. However, being a new area of study, sensor-based activity identification has little survey works. Most researchers struggle to locate benchmark datasets, which hampers their work. This study reviews the state-of-the-art human motion detection utilizing Wi-Fi and sensors. These dataset’s features, activity classifications, sensor types, and devices are described in detail. We've also compiled a list of all possible sensing and application technologies for creating new datasets. Several noise filtering approaches, filter selection, segmentation methods, and window length selection parameters have been detailed. Previous activity recognition approaches have also been summarized and analyzed.

There are also several suggestions for further study into more realistic and widespread circumstances. An overview of motion detection techniques is presented in this paper, as motion has a significant impact on Wi-Fi transmissions. To begin, we'll go over some basic knowledge about Wireless signals and activity types. Following that, we will discuss various methods of detecting mobility, including probability model-based, fingerprint-based, and crowdsourcing-based methods. Furthermore, we demonstrate how to explore the effects of motion in applications that take place in an indoor environment. Finally, in the future, we will release additional applications that will be dependent on Wi-Fi signals.

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