WiFi Sensing with Single-Antenna Devices for Ambient Assisted Living

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ABSTRACT

The absolute coverage WiFi networks is higher than it has ever been and WiFi sensing offers a device-free, contactless alternative to intrusive wearable devices for a variety of applications, in particular for ambient assisted living (AAL). However, a majority of sensing systems proposed in literature use multiple antennas for sensing, resulting in high cost that hinders development of such solutions in real life. This work surveys existing single-antenna systems as a low-cost solution in an AAL scenario. The capabilities of these systems are examined regarding their practical applicability based on testing in AAL environments, leveraging multiple links (i.e. transmitter-receiver pairs) and considering mobile and repositioned receivers. It is found that while the AAL use-cases of respiration monitoring, fall detection and activity recognition are realised by existing systems, further testing in realistic AAL environments with the inclusion of activities of daily living is needed. Additionally the full use of multiple links and consideration of a mobile receiver is still rare, but shows promising improvements. A multi-task system enabling all three applications is discussed using the Model for Ethical Evaluation of Socio-Technical Arrangements (MEESTAR). We suggest an ethically sensitive use, but identify a need for mitigation strategies to address privacy-related concerns of potentially unwilling users.

CCS CONCEPTS

• **Human-centered computing** → Ubiquitous and mobile computing systems and tools; • **Security and privacy** → **Social aspects of security and privacy**; • **Applied computing** → **Health informatics**; • **Hardware** → **Wireless devices**; **Sensor devices and platforms**; **Sensor applications and deployments**.

KEYWORDS

WiFi sensing, ambient assisted living, ubiquitous computing, social aspects of security and privacy

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1 INTRODUCTION

Recent years have seen the rise of technologies using reflected WiFi signals to observe the environment of a transceiver pair. As WiFi signals propagate through the environment they are reflected by static objects like furniture and walls, as well as dynamic objects like humans. The effects of such objects can be observed in the signal at the receiver expressed in the channel state information (CSI) as the change in amplitude and phase. Compared to the received signal strength indicator (RSSI) used in early systems, CSI provides a richer data source [15], enabling the recognition of finer-grained movements. These technologies, broadly gathered under the term *WiFi sensing*, offer valuable characteristics when compared to dedicated sensor devices or wearable sensors, as they require no direct contact or optical line of sight with the tracked object. Furthermore their possible range is only restricted by the reach of the radio signal, resulting in relatively large sensing areas. Compared to camera-based solutions, it is privacy-preserving and often low-cost with a mass market for commercial-off-the-shelf (COTS) WiFi devices. While other wireless sensing technologies based on Ultra-wideband (UWB), mmWave-Radar and LoRa-WAN, have gained interested in the recent past, WiFi is still vastly more ubiquitous and subsequently has high potential for sensing purposes using existing infrastructure.

Various WiFi sensing applications have been proposed, especially in the field of ambient assisted living (AAL). AAL encompasses methods, concepts, services and technologies targeted at assisting people in care in their everyday life. Those primarily include people with disabilities and the elderly, who are potentially in need of medical support and monitoring. Goals for AAL include improving safety, autonomy, mobility and participation for people in care. It also tries to increase resource efficiency to counteract the effects of demographic change in an ageing society [30]. The most widely explored applications of AAL include sleep monitoring, fall detection, respiration monitoring and language assistants.

Many existing WiFi sensing systems focus on health related use-cases [19, 20, 23, 43]. In order to practically implement the capabilities of these systems to an AAL scenario, an evaluation of these systems is needed taking into consideration specific AAL requirements. This would shed a light on the shortcomings of existing systems and inform the development of new systems to be used in AAL. More specifically, the following areas were identified as requirements for a practical application of AAL:

Hardware: As a pre-requisite of WiFi sensing, the collection of CSI data from devices has been a limiting factor in past research, since CSI does not get reported by default on WiFi chipsets [15]. Data collection subsequently mostly relied on the modification of firmware starting with the Linux 802.11n CSI Tool [13], allowing extraction of CSI information from Intel Wireless Link 5300 network-interface cards. A list of extraction tools can be found in table 1. Modifying firmware of specific chipsets as an extraction method inherently limits the range of devices that can be used for WiFi sensing. With the promise of leveraging existing infrastructure and providing low-cost solutions, this results in a limited choice for the implementation of WiFi sensing to practical AAL applications. Access points (APs) with multiple external antennas and Mini-PCs equipped with NICs also using up to three antennas are comparatively expensive. In connection it is likely only few of these type of devices are placed in a single apartment, with their placement being limited by their primary function. In contrast, the rest of the WiFi-enabled devices use a single antenna and serve a wide variety of functions. Those include smart speakers, environmental sensors, smartphones, smart plugs. A multitude of those devices might already exist in AAL environments, possibly scattered or repositioned periodically (e.g. a smartphone). The antenna of these devices is often internal with a limited range compared to an external antenna, with more noise introduced to the signal. As equivalents of these type of single-antenna devices, the ESP32 microcontroller from Espressif, the mono board computer Raspberry Pi and and the Nexus 5, 6 and 6P smartphones with their corresponding extraction tools are examined in this work. With the exception of the smartphones, they are all low-cost, thus lowering the financial barrier for the introduction of new devices.

Table 1: Commonly used CSI extraction tools and devices

CSI Extraction Tool	Release	Device	E.g.	1 Rx Antenna	Cost ≈
Linux 802.11n CSI Tool (Intel Wireless Link 5300)	2011	Mini-PC/Laptop	[44]	○	>100$
		Hummingbird board	[10]	○	330$
Atheros CSI Tool	2015	Various Routers	[45]	○	>100$
		COMPEX WPJ558	[20]	○	100$
ESP32 CSI Toolkit Wi-ESP	2020 2020	ESP32	[3]	●	3$
Nexmon	2018	Smartphones	[27]	●	300
		Raspberry Pi since 3A+	[23]	●	50$
		Router RT-AC86U	[7]	○	150$
AX-CSI	2021	Router RT-AX86U	[11]	○	250$

● := yes, ○ := no

Application: Other than hardware and cost considerations for implementation of a WiFi sensing system to an AAL scenario, its use-case needs to be relevant to people in care or needing assistance. Furthermore the capabilities of a sensing system enabling such an application need to be evaluated in a realistic environment with the sensing target performing their actions in the most realistic way possible.

Sensing Setup: Ma et al. [28] identified cross-device sensing as a challenge, yet noting its ability to improve performance, efficiency and robustness, as well as help the generalization of WiFi sensing. Using multiple transmitter receiver pairs, each forming a sensing link, simultaneously for sensing is difficult due to synchronisation but offers great potential. This is more relevant with single antenna devices, where limited spatial resolution is available and differences between two antennas (e.g. phase offsets) can not be used. Secondly, the repositioning of sensing devices need to be considered. This includes both movement of the receiver during sensing - relevant for smartphones - and also rearrangement of receivers (Rx) relative to the transmitters (Tx) or joint movement of both.

Recently Hernandez and Bulut [18] surveyed WiFi sensing with a focus on edge machine-learning and Chen et al. [5] reviewed the challenges and solutions in cross-domain WiFi sensing. While these and previous surveys offer some practical considerations like computational burden, energy consumption [18], interference from additional movement or other electromagnetic sources [5], none of them discusses specific hardware used in the sensing systems. Without this differentiation, a system using multiple external antennas is considered equal to one relying a single onboard antenna, with much less spatial resolution and noisier data. Similarly the amount of receiving devices and their positioning or mobility in the literature was not reviewed. Furthermore, the reviewed systems were primarily examined through their use case, without considering their testing environment, activities performed during sensing and requirements for deployment. Lastly the ethical, legal and social implications (ELSI) were not discussed following a formal model for evaluation.

This work uniquely addresses these shortcomings by conducting a survey on works using single-antenna devices, providing AAL as a concrete context for evaluation, reviewing the applications regarding their testing environment and activities performed, giving new criteria differentiating between sensing setup and also being the first to use a formal model for the evaluation of ELSI. Notably signal processing techniques and sensing algorithms are not focus of this work, as they have been well covered for WiFi sensing in general by existing surveys [5, 18, 28]. The rest of the paper is structured as follows: the selection criteria for the literature review are first explained in section 2. Section 3 presents the analysis of the literature review. Following this in section 5, the applicability of single-antenna WiFi sensing, applications of WiFi sensing in AAL and an ELSI evaluation following the Model for Ethical Evaluation of Socio-Technical Arrangements (MEESTAR) are discussed.

2 LITERATURE SELECTION

For inclusion of only sensing systems using single-antenna devices the search terms were limited to a mention of the extraction tool Nexmon or the ESP32 microcontroller. These technical terms were chosen over a broad mention of a single-antenna system, due to the fact that this characteristic is not reliably reported in literature. In contrast the hardware and extraction tool used are commonly referenced. Taking into consideration the availability of extraction tools for single-antenna devices (shown in table 1) this approach still provides a comprehensive selection. The resulting works were filtered to only include recent publications and remove duplicates. Irrelevant publications that were remaining were manually excluded. The results of each step can be seen in fig. 1.

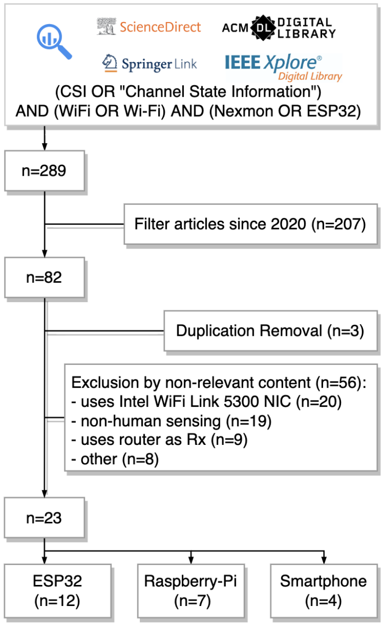

Figure 1: Selection flow of surveyed works

Most of the excluded works were discarded because the sensing is performed by an Intel Wireless Link 5300 NIC which has three antennas and therefore is not focus of this work. More exclusions came from systems with a non-human target for sensing, i.e. objects or other devices, and nine works were excluded because they used multi-antenna routers. This resulted in 23 publications (full list shown in table 2) being discussed in the literature review.

3 SINGLE-ANTENNA WIFI SENSING SYSTEMS

In this section, the included works are examined regarding the areas identified as required for a practical implementation in section 1. First we examine the hardware used for the receiver as it is the most impactful device for the system design. Then we investigate the application of each system, which includes their use-cases, the environment for the testing and the activities performed by the target during the testing. Finally, each work is examined regarding the sensing setup, encompassing its use of multiple links and the impact of repositioning devices within their testing environment.

4 HARDWARE

Of the 23 included works, more than half is based on the ESP32 (57%) followed by the Raspberry Pi (26%) and only four (17%) using a smartphone as sensing device. Four of the thirteen publications for the ESP32 are published by Hernandez and Bulut, the developers of the ESP32 CSI Toolkit [15]. The Nexmon extraction tool is available since 2018 [36], compared to the ESP32 extraction tools released in 2020 [3, 15]. Considering this difference ESP32-based systems appear to be more popular for single-antenna WiFi sensing than ones based on the Raspberry Pi or Nexus line.

4.1 Application

4.1.1 Use-Case. Examining the resulting works nine publications have directly health related use-cases [2, 18, 19, 23, 24, 27, 32, 37]. Those include detection of fall events [2, 18, 32, 37], respiration monitoring [23, 27] in the form of breathing rate estimation additionally with abnormal breathing pattern recognition, occupancy monitoring [24] and lastly the tracking of rehabilitation exercises [19]. Other use-cases are human presence detection [2], motion detection [33], crowd counting [6, 14, 22, 24] and user identification/authentication [4, 9, 29, 41]. Localisation, also popular in multi-antenna WiFi sensing [5], is only investigated in combination with other use-cases. Similarly only a single system enables gesture recognition. Both use-cases have a significant amount of research attention in WiFi sensing in general [28] and together with presence detection are comparatively underrepresented here. This marks a separation of use-cases from multi-antenna WiFi sensing compared to single-antenna. A clear separation of use-cases based on the device used can not be observed.

4.1.2 Setting. Most of the systems (48%) use an office or laboratory environment for their testing. About a third (35%) target a residential setting and experiments are conducted in either a real or emulated furnished apartment. This is inherently more challenging as furniture and walls are likely to be placed less regularly resulting in more complex signal reflections. Both types of settings potentially offer applicability to AAL either for at-home assistance or care facilities.

4.1.3 Activities. The activities performed during sensing, either with the activity being the focus or incidental, include general (non-)movements such as sitting, standing, walking and lying and more specific activities such as falling, washing dishes, holding up hands etc. Surprisingly even among systems targeting activity recognition, few offer clear selection criteria for the activities they chose, or argue for the relevancy of those activities in their chosen setting. Activities of daily living (ADL) are a non standardised variety of activities performed by users in their every-day life. As such they are highly relevant in assistance scenarios, where an application needs to be integrated in existing user routines. Only the work by Hernandez and Bulut [18] offers a comprehensive selection of such activities.

4.2 Sensing Setup

4.2.1 Multi-Link. The integration of CSI data from multiple devices simultaneously is only done by Wi-Cal [6] and WiFederated [17]. The first is using 4 separate links , i.e receiver transmitter pairs, for localisation and counting. For this the data is collected locally on all devices. Six different machine learning methods, e.g. based on deconvolutional neural networks (DNN) and the Light Gradient-Boosting Machine (LightGBM) are applied and compared using a workstation PC later on. In their testing the links are arranged with each line-of-sight (LOS) between receiver and transmitter going across the entire sensing area. This allows for all links to separately localise people with an average accuracy of 84% and count the amount of people present with a mean absolute error (MAE) between 0.55 and 0.82. This is then improved to 98.1% accuracy and 0.41 MAE when using all links simultaneously. This

Table 2: List of included works

		Application					Sensing Setup	
Reference	Rx Device	Use-Case	Environment	Activity	Performance	ML Model	Multi-Link	Repositioning
WiFederated [16, 17]	ESP32	Activity Recognition	Apartment	Sitting, Standing + Transition between	Acc.:96.4%	Amplitude + DNN	●	○
Hernandez and Bulut 2020 [15]		Human Activity Detection	Office	Movement relative to Rx/Tx (depth and direction)	Strongly varying based on scenario	Raw (A,ϕ) + DNN	○	●
Hernandez and Bulut 2023 [18]		Localization Activity Recognition Fall Detection	Apartment	Washing Dishes, Oven, Fridge, Writing at Table, Open Closet, Wash Hands, Use Stairs, Sofa, Walking in Living Room	Acc.:71.24%	Amplitude + DNN	◐	◐
Wi-PT [19]		Physical Rehabilitation Tracking	N/A	Wrist movement, Finger movement, Whole-body movement, Equipment	Acc.: 85.21%/97.13%/ 80.65%/93%	Raw (A,ϕ) + DNN	◐	◐
Zeeshan et al. 2022[42]		Localization Activity Recognition	Residential Room	Sit-Down, Stand-Up, Standing, Wave-Hands	Acc.: 99%	Amplitude + CNNs	○	○
Wi-CaL [6]		Human Counting; Localization	Office	Walking	Count: 0.41 MAE Position: 98.1 Acc.%	Stat. Features + LGBMR/LGBMC	●	○
Car-Sense [14]		Occupancy Detection; Crowd Counting	Car	Sitting	Acc.:85%	Stat. Features + KNN	○	◐
Sahoo et al. 2023 [32]		Activity Recognition	Laboratory	Walking, Jumping, Falling, Sitting	Acc.: 70%	Stat. Features + SVM	○	○
Natarajan et al. 2022 [31]		Occupancy Detection Activity Recognition	Apartment	Sitting, Standing, Lying	Acc.: 99.4%	Stat. Features + RF	◐	○
Wi-Monitor [22]		Human counting	Office	Walking	Acc.: 76.5%	Raw (A,ϕ) + DNN	○	○
Makwana and Shaikh 2022 [29]		User Authentication	Residential Room	Walking, Stationary	Acc.: 64%/85%	Various (AE, STE) + LSTM	○	○
Sandurawan et al. 2021 [34]		Human counting	Outdoor	Standing	Acc.: 79%	Raw (A,ϕ) + DNN	◐	○
Kumar et al. [2]		Fall Detection; Presence Detection	Laboratory	Falling	N/A	N/A	○	○
COVID-Safe [24]	Raspberry Pi 3B+, 4, 4B	Human Counting	Elevator, Office	Standing/not reported	Acc: 93%/97%	Stat. Features + SVM	◐	◐
Turetta et al. 2022 [41]		Identity Recognition	Office	Sitting at desk	TN: 99% TP: 98%	Amplitude + CNN	○	○
Wi-COVID [23]		Respiration Rate Monitoring	Residential Room	Sleeping, Sitting	N/A	Amplitude + custom model	○	○
Schäfer et al. 2021[37]		Activity Recognition	Residential Room	Empty, Lying, Sit, Sit-Down, Stand, Stand-Up, Walk, Fall	Acc.: 97%-99.7%	Raw (A,ϕ) + LSTM	○	○
Ebraheem et al. 2022[9]		Identity Recognition using Lip Movement	Office	Standing	Acc.: 94%	Stat. Features + SVM	○	○
Tian et al. 2022 [39]		Activity Recognition	Office	Stand, Bend-Over, Squat, Hold-Up-Hands	Acc.: 95%	Stat. Features + SVM	○	○
WiPhone [27]	Nexus 5, 6, 6P	Respiration Rate Monitoring	Apartment	Lying, Sitting	MAE: 0.31 bpm	Amplitude + Custom model	○	○
WiCapose [4]		User Authentication	N/A	Tapping fingers on smartphone	Acc.: 98.3%	Raw (A,ϕ) + DNN	○	○
Li et al. 2020[25]		Gesture Recognition	Laboratory, Large Hall, Office	Push-Pull, Sweep, Clap, Slide, Circle, Zigzag	Acc.: 92%	Stat. Features + DTW	○	◐
CSI:DeSpy [33]		Human Motion Detection	Hotel Room	Physical activity	Acc: 95-100%	PCA + DBSCAN	○	○

● := criteria fully met, ○ := criteria not met

◐ := criteria is met partially (uses multiple devices separately or does not consider mobile receivers only varying placements)

Symbols/Acronyms: A (CSI Amplitude), ϕ (CSI Phase), DNN (Dense Neural Network), LGBMR/LGBMC (Light Gradient Boosted Machine Regressor/Classifier), LSTM (Long Short-Term Memory), SVM (Support Vector Machine), DTW (Dynamic Time Warping), DBSCAN (Density-Based Spatial Clustering of Applications with Noise), KNN (K-Nearest Neighbours), RF (Random Forest), PCA (Principal Component Analysis), AE (Autoencoder), STE (Short-Time Energy)

is probably an ideal scenario for multi-link sensing as the overlap between the sensing area of individual links is very high, with all covering the same space. WiFederated on the other hand proposes a collaborative approach using federated learning. This allows for a global prediction model, dynamically selecting links (referred to as clients) and sharing knowledge between locations. Five other works [18, 19, 24, 31, 34] also deploy multiple links for their sensing experiments. But while CSI data is gathered from all of them, only a single data stream is ultimately used for the prediction. This link selection process is done after the fact. The arrangement of the links is also done with minimal overlap (unlike Wi-Cal) in the case of Hernandez and Bulut 2023 [18] to cover the largest area of a residential apartment using three links. Their work shows this also helps in the recognition of activities in specific areas as the most qualified link, i.e. the closest, will allow for higher prediction accuracy. Nevertheless, their studies demonstrated a theoretical upper limit improvement of +25.6% (89.14%) over the most qualified single link, with ideal selection. In the worst case the accuracy drops -41% (29.65%), as all links need to make a correct prediction for a given class. This shows potential for multi-link sensing even in scenarios without high overlap between links, but highlights importance of link selection. This potential improvement is also confirmed by the results of Wi-PT [19]. The system Covid-Safe, while using two links for one test scenario, does not explore combined usage [24].

4.2.2 Repositioning. The criteria of repositioning in this review is met when a work considers a mobile receiver in a single setting. It is partially met when multiple placements of a receiver are tested within a setup and compared. This includes repositioning of both transmitter and receiver joint or separate. If the target changes,i.e. the activity is performed at a different location in the environment or another activity is performed, this constitutes a different setup. There is an overlap with the multi-link criteria, when multiple links are used interchangeably for the same task, therefore indirectly testing the repositioning between link locations. Of the 23 works examined six (26%) consider different placements of sensing devices. This is similar to the 30% considering multiple links. Furthermore 33% of works using the ESP32 test varying placements, while only two works, one based on the Raspberry Pi (17%) and the other based on the Smartphone (25%) does so. This could be explained with the microcontroller having a relatively low power consumption [18] and being low-cost compared to the other devices (as shown in table 1). This enables more flexible placement of sensors when running on battery power and also makes it easier to place multiple devices in a single experiment. In the testing of their system, Hernandez and Bulut [15] consider joint repositioning of both transmitter and receiver, the repositioning of only the receiver and a mobile receiver. For joint repositioning, they note drastic changes when repositioning slightly while maintaining distance. When only repositioning the receiver, they demonstrate a single placement is consistently achieving higher accuracy over the others. This placement notably is not one with the LOS covering the area of the movement directly, but one placed in a corner. Lastly they show a mobile receiver performing better than static positions at start and end of the motion. In their latest publication, Hernandez and Bulut [18] show strongly varying accuracy for specific activities (walking up/down stairs, sit on sofa, walk around) when comparing between three sensing links. Their results show that while all the three activities were performed close to and in direct LOS of one of the three links used in the study, this link (Link 3) only leads to the best recognition performances for one of the three activities. The other two activities are being more accurately predicted by one of the two links further away and with the activity being performed behind their receiver. In an opposite direction, Car-Sense [14] observes that exposure to the WiFi signal increases robustness and accuracy, due to a more reliable time domain for CSI. Li et al. [25] identified Tx-target-distance, Rx-target-distance and position of the target relative to LOS as impact factors on the performances of gesture recognition. They found that decreasing Tx-target-distance might worsen accuracy and increasing Rx-target-distance will improve it. They also show that positioning the target directly in LOS between Rx and Tx has the highest accuracy. In summary the combined findings of the examined works offer the following insights:

(1) Rx-Tx-, Tx-Target- and Rx-target-distance are not conclusive metrics for optimal positioning in complex environments
(2) More accurate results might be achieved when the tracked activity is not in Rx-Tx-LOS, but rather behind the receiver
(3) Mobile receivers might offer good improvement over static positions

5 DISCUSSION

5.1 Applicability of Single-Antenna WiFi Sensing

From the presented results in section 3 it is apparent that single-antenna WiFi sensing systems yielding promising performances for the use-cases relevant to AAL exist. They mainly use low-cost hardware like the ESP32 and or a Raspberry Pi. For leveraging existing infrastructure smartphones as mobile receivers are very promising, but only a handful of works are based on the Nexus 5, 6 or 6P. The latest of these models has reached its end of life in 2018 [1]. Being the only smartphone available for CSI extraction this is concerning as a large group of existing devices are potentially not authentically covered by research. Without new extraction tools that enable CSI extraction from smartphones, we suggest the exploration of using a battery powered ESP32 microcontroller as dummy-replacement in mobile receiver use-cases as an alternative to the Nexus line. Connected to this are the efforts of enabling WiFi sensing on a majority of devices by the IEEE 802.11bf amendment to the IEEE 802.11 standard [8]. If adopted this would abruptly increase the amount and variety of devices available for sensing. The research has largely been driven by multi-antenna devices, with just systems using the Intel Wireless Link 5300 accounting for more than 1000 publications according to the developers of the Linux 802.11n CSI tool [12]. This is in stark contrast with the 23 works included here and a maximum of 37 of works citing the Nexmon extraction tool before 2020 for an approximate total of 60 publications using single-antenna devices. This indicates more research is needed on WiFi sensing using single-antenna devices.

5.2 WiFi Sensing for AAL

From the reviewed works in section 4.1.1, the use-cases of fall detection, respiration monitoring and activity recognition have been identified as most relevant in an AAL scenario. Within a smart home or assisted living setting for elderly people or people with disabilities these three use-cases could provide valuable contextual information on the status of people within range. The monitoring of vital signs, fall events and activity tracking of people in a care setting is traditionally provided by healthcare professionals or relatives. Chronic respiratory diseases affect 1 billion people worldwide and daily respiration monitoring plays an important role in early diagnosis and treatment [43]. Traditional solutions require users to carry intrusive devices and are impractical for long-term monitoring in an at home setting [43]. Previous work has shown a reluctance in elderly people to wear devices at all times [26], which possibly could be overcome with contactless sensing systems. Furthermore, falls account for the most of accidental death and injury in older adults. Overall 30% of people of age 65 or older experience a fall resulting in injury or death each year[40]. This problem is exacerbated by a large amount of seniors living alone, making falls possibly go undetected for hours [40]. Existing wearable solutions are hindered by the reluctance to wear a device at all time and many vulnerable people suffering from memory problems [40]. Passive fall detection solutions might be able to boost acceptance, prevent injury and relieve elderly people from the burden of handling and charging wearable devices. Tracking human activities indoor has been employed to monitor and study people's behaviours, such as elderly and disabled people's daily routines [26]. It can also provide human computer interface for visually impaired people to explore and navigate surrounding areas and receive location-based services [38].

Sensing systems enabling multiple use-cases simultaneously are referred to as multi-task sensing systems [5]. Some use-cases have tangential features, offering easier opportunities for combination. For example localisation, activity recognition and fall detection have been combined by multiple works, as they share strong similarity in features [15, 18, 31, 42]. Nevertheless, true multi-task sensing still remains an open challenge even with multiple antennas [5]. While fall detection and activity recognition have been combined in the past, no system so far has included respiration monitoring. A true combination could provide an age appropriate assisting system for people in care. Development of such a system however raises serious moral questions as it targets a vulnerable group within a private environment using complex and largely invisible technology. To discuss the desirability of such a system and start an iterative process of ethical evaluation, we now take a closer look on the implications of a fictive combined deployment. We consider the case of a multi-link system using single-antenna devices with mobile and non-mobile receivers.

5.3 Ethical, Legal and Social Implications (ELSI)

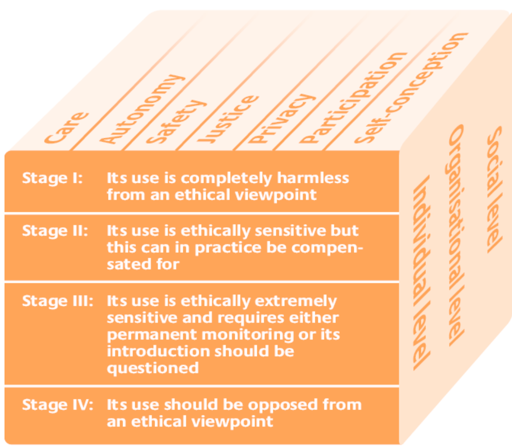

Figure 2: MEESTAR: x-axis: dimensions of ethical evaluation; y-axis: stages of ethical evaluation; z-axis: levels of ethical evaluation (Original: Manzeschke et al. 2015 [30]).

In order to evaluate the ethical, legal and social implications of a sensing system in AAL as described in the previous section, the Model for Ethical Evaluation of Socio-Technical Arrangements (MEESTAR) [30] was followed. It focuses on the social and normative influence of a given technology and the socio-technical arrangements affected by it. It was developed specifically for AAL in a homecare setting and has been used in other works for the evaluation of ELSI [35]. It is based on the concepts of dimensions, levels and stages of ethical evaluation. An overview of the MEESTAR can be seen in Fig. 2. We employ a singular focus on the individual level for evaluation, without inspection of social or organisational perspectives. This choice was made as the focus lies on the individual user, for instance an elderly person in an assisted living facility, interacting with the system and also allowing for varying environments or integration scenarios. Going through every dimension for the proposed system results in the following considerations:

Care: The proposed applications give additional monitoring in the absence of caregivers. Early detection of abnormal deviation in daily routines, breathing rate and the detection of falls could provide more effective care. Furthermore people in care with a requirement of permanent monitoring may view existing wearable solutions as patronising or negatively paternalistic. This is potentially alleviated with WiFi sensing as no device on the user is needed. Passive detection could also help with situations involving shame of asking for help in the inability of self-help.

Autonomy: At the same time passive monitoring systems take away the decision of reporting incidences from the users. When a persons decision-making becomes questionable or even untenable, this could be wanted, but it limits their autonomy. Conversely for elderly people or people with disabilities who rely on caregivers and can not afford existing monitoring solutions, it could give back autonomy, as this task is automated. Overall the fear of losing independence through AAL systems is low in seniors [21].

Safety: While the proposed systems might objectively provide as much safety as existing wearable solutions, the subjective feeling of security could be lessened as the physical objects within reach of the user possibly provide more confidence in the system. Yet seniors do not note visibility as an important feature [21]. Furthermore the proposed applications are much more complex and potentially harder to understand when compared to a simple wearable emergency button. But as they require no interaction the ease-of-use, an important feature for seniors [21], is unaffected.

Justice: Due to the wide availability of WiFi devices and the ability to share them, WiFi sensing solutions could give more people access to real-time health monitoring and potentially medical help in an adverse event. This is particularly true for socially isolated people with low-income living alone.

Privacy: WiFi sensing systems collect highly sensitive data about people potentially unknowingly moving within their transmission range. With the ubiquity of WiFi networks and the through wall sensing capabilities of these systems this problem is exacerbated. While existing systems do not identify individual people on biometric information, they potentially allow extensive tracking and identification through contextual information [4, 9]. In comparison with computer vision based systems, they give more anonymity to users. But because most of the applications work on already installed commodity hardware, the potential for misuse and invasion of privacy of non-users could be enormous. Supporting this, seniors report local processing as a feature of high importance, but still mostly find sharing information with the primary care person acceptable with a moderate fear of an invasion of privacy [21].

Participation: These applications could potentially give more mobility to people reliant on health-monitoring and increase their participation in social- and work-life. It could also make real time health-monitoring a responsibility of public network infrastructure.

Self-conception: With the potential reduction in the number of dedicated devices used for health monitoring, users might experience a less medicalised and technically assisted image of ageing. Physically less intrusive health-monitoring technology could shift into the periphery of users.

With all evaluation dimensions considered benefits in all dimensions could be identified. However restrictions in the privacy of users and non-users suggest a trade-off between conflicting interests. While great potential for abuse of WiFi sensing systems exists, we suggest their use as an ethically sensitive technology, with mitigation strategies being deployed in practical applications (MEESTAR ethical evaluation stage II). For example with the potential risk of unintended tracking, some mitigation strategies can be deployed for the preservation of the privacy of users and non-users. Firstly, tracking systems can include spatially fenced areas using its localisation information, only for which tracking and sensing information is given. This could include the perimeter of an apartment but also private areas for caregivers could be excluded. Additionally sensing links could be placed in a privacy-preserving manner, purposefully limiting sensing to the intended area. This is challenging since as presented in section 4.2.2, there are varying results regarding the optimal positioning in indoor environments. Lastly WiFi allows shaping of the signal propagation known as beamforming for better transmission rates. This could potentially be used for limiting wireless sensing capabilities to the vicinity of active devices in the network. Also antenna gain could be adjusted for a more limited WiFi coverage, reducing the risk of unintended tracking outside the designated sensing area.

6 CONCLUSION

WiFi sensing using single antenna devices offers great possibilities when applied in the field of ambient assisted living. Single-antenna WiFi devices are already present in many peoples homes such as smartphones and smart-home device. These devices could potentially be leveraged in a AAL sensing system. This work reviewed existing single-antenna WiFi sensing systems regarding their practical applicability in AAL and proposed a multi-link and repositioning criterion for a better understanding regarding sensing setup used. From the existing applications of single-antenna WiFi sensing, the three applications of respiration monitoring, fall detection and activity recognition were identified as directly relevant in an AAL setting. However only few systems conduct testing in a close to real-world AAL setting and include activities performed by people through their everyday life. So far no existing system leverages multiple links simultaneously while using mobile receivers or considering repositioning of the devices. The implications of such a system enabling multi-task sensing for respiration monitoring, fall detection and activity tracking were discussed using MEESTAR. The proposed ethical evaluation stage II suggests the need for the development of further mitigation strategies and sustained efforts in ethical evaluations of WiFi sensing systems. With the unique capability of eventually re-using existing infrastructure while providing a variety of assisting applications for the elderly and people with disabilities, WiFi sensing has great potential to improve peoples care and daily life.

Following the review of single-antenna sensing systems, a multi-link system for a simultaneous application of respiration monitoring, fall detection and activity tracking will be the focus of future work. For this purpose, testing in an AAL setting and including activities of daily living are primary factors for experiment design. Finally the ethical, legal and social implications will be iteratively evaluated using the MEESTAR model.

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