(http://www.sars.gov.za/TaxTypes/PAYE/Pages/PAYE-Annual-Reconciliations.aspx)

(http://www.sars.gov.za/TaxTypes/PIT/Tax-Season/Pages/default.aspx)

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Monitoring health using WiFi sensing and machine learning

Healthcare is a big social and economic issue. The need to assist people with disease, and mental and physical disabilities places increasing demands on limited resources for around-the-clock monitoring. We used LabVIEW and universal software radio peripheral (USRP) to create a passive WiFi sensing system that can detect body movements and vital signs of a subject through walls and without any physical contact.

The primary aim of health-related artificial intelligence (AI) applications is to analyse the relationships between prevention or treatment techniques and patient outcomes. Such systems need to work with accurate signal data about instant and long-term activities that make up an individual's pattern of life information. Engineers are currently exploring solutions for the following challenges in residential healthcare:

Vital signs: Respiration and heart rate data can be accurately measured with a chest belt, electrocardiogram, or photoplethysmography instruments. However, it is not practical to use such costly and inconvenient clinical instruments for daily monitoring scenarios in residential healthcare.

Life threatening events: Events like falling and slipping are often main causes of death in residential environments, especially for elderly or disabled people. Continuous surveillance can alert care workers when help is most needed.

Daily activities: Monitoring a person's daily activities can offer an abundance of health-related information. Even seemingly insignificant activities like making a cup of tea could provide information on water intake, sugar consumption, and lifestyle. Sensing daily activities at home could unlock new insights for healthcare and human lifestyle research.

Chronic activity level awareness: Decreased physical activity can indicate signs of physical or mental health problems, such as chronic pain or depression. Therefore, a weekly, monthly, and long-term log of activity levels can unlock a wealth of information for understanding root causes and preventative measures for health conditions.

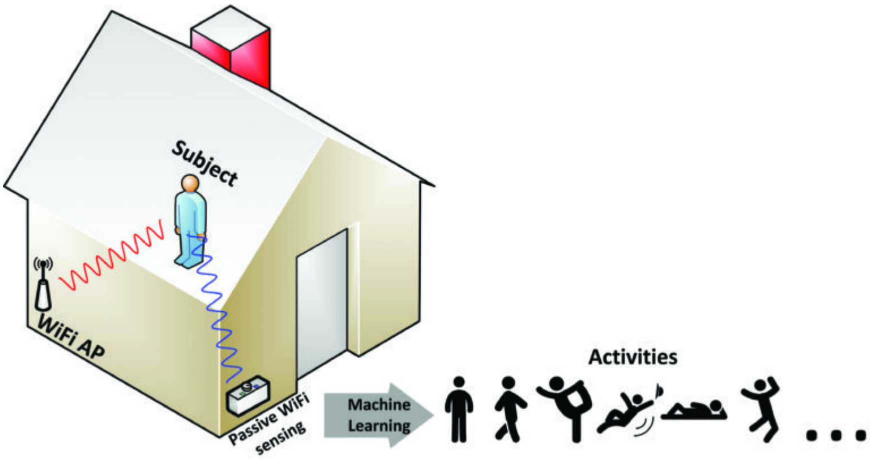

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Fig. 1: Passive WiFi sensing for in-home activity sensing.

The widely adopted detection methods currently used within care homes include wearable devices, camera-based vison systems, and ambient sensors. However, these established options have major drawbacks (respectively, physical discomfort, privacy concerns, and limited detection accuracy).

There is an urgent requirement to develop novel monitoring solutions which are contactless, accurate, and minimally invasive. This inspired research into passive WiFi sensing systems, and led us to adopt LabVIEW and USRP for rapid prototyping.

Passive WiFi sensing technology

The concept of passive WiFi sensing for residential healthcare is a natural extension of research at University College London, which proved the concept of passive WiFi radar. Here, the term passive refers to the fact that users do not need to actively transmit a wireless signal to receive the radar echo. Instead, the passive WiFi prototype, which was based on National Instruments (NI) software defined radio (SDR) solutions, leverages the wireless signals that already swamp our urban airways. Because passive WiFi radar is "receive only", it is low power, unobtrusive, and completely undetectable. This is a major benefit to military and counterterrorism scenarios.

NI technologies best fit our research needs. The NI SDR solution was used to transition from concept to prototype to deployment faster than alternative approaches and is very versatile. We could repurpose the original prototype for entirely new applications, including health and activity monitoring in retirement and nursing homes. However, scaling the prototype to fit the needs of residential healthcare required advancements in two key areas: signal processing and machine learning.

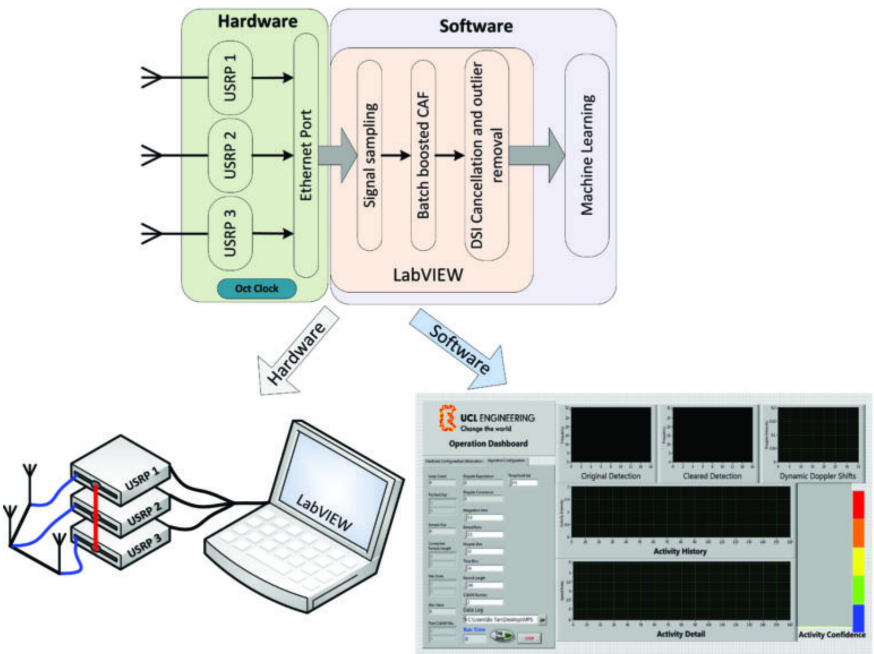

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Fig. 2: USRP-based concept system design and architecture of hardware and software.

Signal processing

Passive WiFi sensing is a receive-only system that measures the dynamic WiFi signal changes caused by moving indoor objectives. The indoor multiple path propagation negatively impacts the wireless communication, but gives an opportunity for interpreting human activities. Due to the dynamic movement of a subject, the dynamic path presents time variation on the angle of arriving (AoA, θ) and propagation delay (τ) that correlate with the subject's movements.

If we take an incisive look of θ and τ, the phase change of the receiving signal can present all of them. We can use frequency to measure phase changing rate during the measurement duration and Doppler shift to identify movements. We can discern real-time, high-resolution Doppler shifts for a given duration using batch processing boosted cross ambiguity function (CAF) analysis.

We also use the phase of each batch to identify small displacements of a subject, which is often used for inconspicuous body movement like breathing. Most commercial wireless network interface cards cannot deliver raw RF signal samples, which is why we chose USRP and LabVIEW software to capture, process, and interpret the signals.

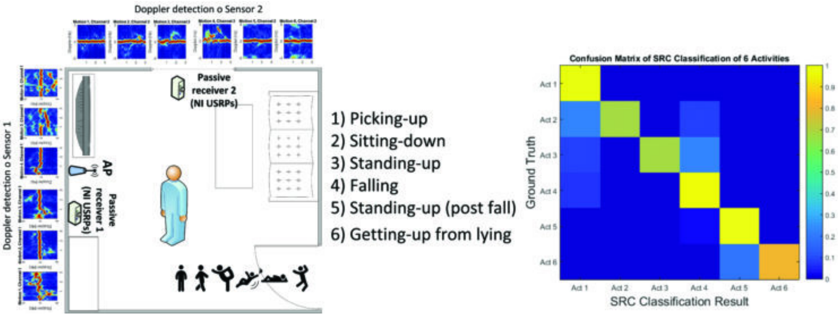

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Fig. 3: Recognition of six daily activities based on passive WiFi sensing.

Machine learning

We can easily interpret some captured signals. For example, we can directly link the periodic change of batch phase with respiration rate. However, others may be difficult to understand visually. An example is the Doppler-time spectral map associated with gestures like picking things up or sitting down. Thus, we introduced machine learning to discover the link between the Doppler-time spectral map and physical activities. In practice, we tested principle component analysis (PCA) and singular value decomposition for Doppler-time spectral mapper feature extraction. Then we feed the features to support vector machine and sparse representation classifier (SRC).

The resulting classifiers show a promising capability of recognising the daily activities from Doppler-time spectral map. Besides the classification of the instant activities, the machine learning method can also model the pattern of a resident's lifestyle by interpreting the long-term passive WiFi activity data.

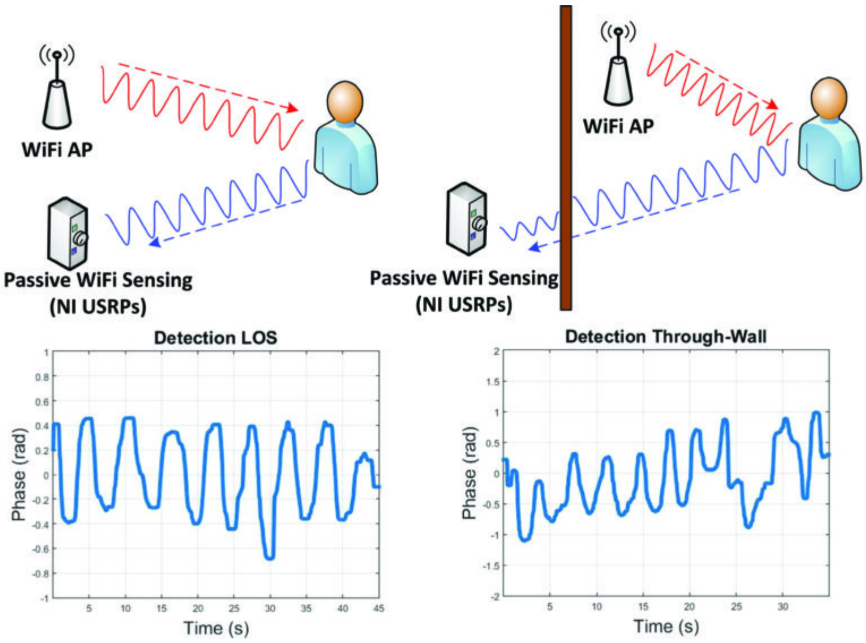

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Fig. 4: Through-wall respiration detection with USRP-based passive WiFi sensing.

Building the proof-of-concept system

To prove the concept, we built a prototype system based on USRP SDR and LabVIEW. The USRP captures the raw IQ samples and delivers them to our LabVIEW application for fast signal processing. LabVIEW delivers incredible flexibility for rapid prototyping, so we can adjust signal processing parameters to meet our exact requirements, whilst making the best use of multicore processing technologies. We could dynamically change the data arrays we work with, or alter the integration time and batch size of our analysis routines to adapt the system to slow and fast movements. Also, LabVIEW delivers an intuitive software environment, which empowered us to quickly integrate signal processing code, presented as subVIs in LabVIEW, for experimenting with new algorithms.

Experimental results

Based on the prototype system, we verified conceptual passive WiFi sensing in two scenarios: activity recognition and through-wall respiration sensing.

Activity recognition

A group of gestures common in residential healthcare have been studied. Fig. 3 (left) shows the extracted Doppler-time spectral map from the two sensors during each gesture cycle. We then applied SRC classification based on the PCA features of each Doppler signature. Fig. 3 (right) shows the behaviour recognition result.

Respiration sensing

As described previously, the phase of the data batches is accurate enough to discern the small body movements caused by respiration. In this experiment, we demonstrated a through-wall breathing detection. To observe the clear periodical signal varying caused by breath, we used a Hampel filter to remove outliers and superfluous information.

Conclusion and impact

Compared to the established monitoring techniques (cameras, wearables, ambient sensors), passive WiFi sensing displays serious advantages:

Contactless and pervasive: The ability to identify activities anywhere WiFi connectivity is available, without the need for any subjects to carry devices.

Diverse and accurate information: The detection of many activities from respiration to body gestures, from casual day-to-day operations to severe events.

Unobtrusive: Because activity information is obtained from reflected RF signals and not images or video streams, we significantly reduce concerns over subject privacy.

Using USRP and LabVIEW has accelerated this research into passive WiFi sensing, leading to innovative advancements, collaborations, more than 15 research publications, and patents. Going forward, we will continue to use the platform to advance passive WiFi sensing in the areas of geometric dependencies and data bursts.

Contact Bo Tan, Coventry University, **bo.tan@coventry.ac.uk (mailto:bo.tan@coventry.ac.uk)**

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