Sensing With Wifi

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Outline

- **Background & motivation**
- FMCW-based systems
  - Wi-See
  - Vital-Radio
- CSI-based systems
  - Keylogger
  - E-eyes
  - Deep learning
- Future of Wifi sensing

Human Activity Recognition

- Human activity recognition is a hot topic of research
- Applications include:
  - Health monitoring (e.g. heart rate measurement, fall detection)
  - Smart home products
  - Internet of things
- Want sensing technique that can be both widespread and unintrusive

Sensing Techniques

- Wearable devices (*active* monitoring)
  - Intrusive to user – impractical
- Camera-based
  - Privacy-invasive
  - Requires line of sight (LOS)
- Possible solution: wireless signals
  - Permeate walls – LOS not required
  - Can be passive and non-invasive

Sensing with Wireless Signals

- Wireless signals can be used to create widespread passive sensing systems
- Many projects have demonstrated this successfully
  - Some use specialized hardware – specifically USRP
  - Others use commercial Wifi products
- Systems using common Wifi hardware would be ideal
  - Take advantage of widepsread existing infrastructure
  - Easy to deploy

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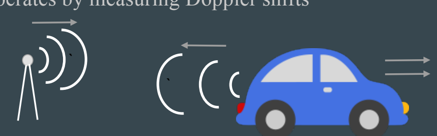
FMCW

- Most systems with specialized hardware utilize FMCW
  - Frequency-modulated carrier waves
- Operates by measuring Doppler shifts



- Frequency of reflected signal modulated by movement of reflector

Specialized Hardware

- FMCW requires a specialized software-defined radio
  - Typically a modified USRP N210

- Expensive (>$1,000) – impractical for ubiquitous sensing applications

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WiSee System

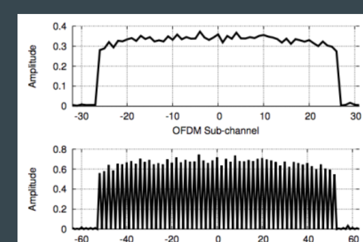
- WiSee project implements sensing system using FMCW on USRPs
- Goal: gesture recognition in homes
  - Increase interface methods for smart homes
  - Line of sight or quiet environment (for voice commands) not needed
  - Example application: changing music in other room while cooking

WiSee: Detecting Movement

- FMCW: movement of target changes frequency of reflection
- At WiFi frequencies, only expect shifts around 10-20 Hz
- Hard to detect with 2.4 GHz or 5 GHz OFDM
  - E.g. 17 Hz shift in 5 GHz system with .5 m/sec gesture
- Tradeoff - higher frequencies yield larger Doppler shift
  - But also more directional, not ideal for NLOS situations

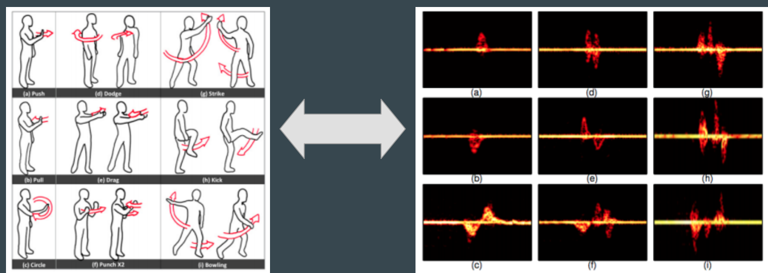
WiSee: Detecting Movement

- Must transform into set of narrowband pulses
- Narrow enough that flat fading can be assumed
  - Greatly simplifies analysis



WiSee: Gesture-Doppler Mapping

- Gestures performed by humans cause distinct patterns in Doppler shifts



WiSee: Gesture Detection

- Doppler Extraction
  - Computes frequency-time Doppler profile of narrowband signal (FFT)
- Segmentation
  - SNR thresholding + clustering
- Gesture Classification
  - Pattern matching w/ positive and negative Doppler shifts

WiSee: Gesture Detection

- System **directly** analyzes pattern of movement and classifies as one of nine gestures
  - E.g. quick movement towards receiver classified as “push”
- Tested in indoor office space and 2-bedroom apartment
  - 94% success rate on average
- Additional features:
  - Via MIMO technology, can identify multiple people in range
  - One person can “take control” of system by performing designated control gesture

WiSee: Strengths

- Robust *macro* gesture detection
- Utilizes prevalent effect (Doppler shift) w/ simple pattern matching classification
- Can use MIMO capabilities to detect multiple humans
  - Requires preamble for specific user

WiSee: Limitations

- USRP needs to transmit continuously – blocks Wifi
  - Could potentially be done on different frequency, but need different hardware
- Specialized hardware is expensive
  - Not easy to deploy into every smart home
- Limited feature set and processing
  - Could be expanded by using techniques like HMM, DTW

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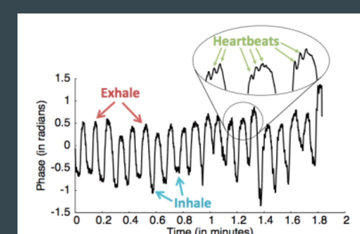
Vital-Radio System

- 2015 project aimed towards ubiquitous healthcare monitoring
- Uses same FMCW technique with modified USRP 210s
- Aim is to monitor heartbeat and breathing rate of one or more people
  - No instrumentation/devices
- Primarily intended for medical centers and nursing homes

Vital-Radio: FMCW Sensing

- Transmits 5GHz signal and analyzes reflections
- Monitors phase of reflection
  - Equivalent to monitoring frequency offset at low frequencies
- Finds fast and slow periodic changes in phase
- Identifies breathing rate and heartbeat



Vital-Radio: Performance

- Can determine distance of objects from transceiver based on phase difference
  - Filters out inanimate objects
  - Can lock onto specific people and track up to 3 at a time
- Works up to 8m away and through walls
- Lower power than WiSee – less disruptive to Wifi
- Tested in indoor office building
  - 99% average success rate for both breathing and heartbeat

Vital-Radio: Limitations

- Data gets mixed if two people are the same distance from transceiver
- Cannot distinguish between moving objects and people
  - Interprets ceiling fans as breathing humans
- Requires people to be quasi-static (not walking around)
- More effective than WiSee, but still disruptive to Wifi and requires specialized hardware

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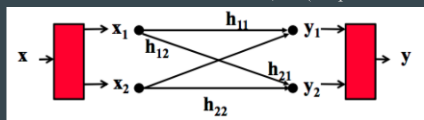
Active vs. Passive Sensing

- FMCW has limitations
- A primary issue is that active sensing interferes with Wifi signals
- Would like to sense passively – without adding signals to local space
- RSS: received signal strength (amplitude and phase)
  - Can make interpretations about medium state based on RSS?
  - Sounds good, but in reality too broad and unstable
  - Averages attenuation of all frequencies in channel
- Need a metric with greater granularity and consistency

Channel State Information (CSI)

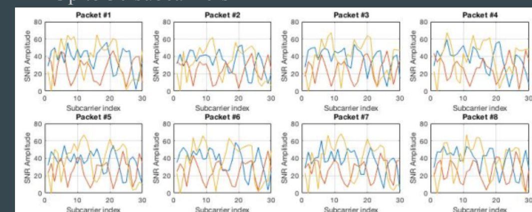
- In a MIMO system, can see RSS of each subcarrier between each antenna pair
- CSI refers to this channel matrix, **H** (amplitude and phase)



- For 802.11n systems, up to 64 subcarriers in up to 4 receiving antennas
- Full CSI matrix provides much more detail than simple RSS
- Sufficient enough to make determinations about the channel medium

Intel 5300 NIC

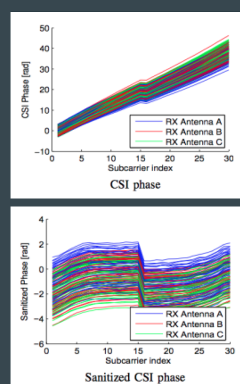
- Intel 5300 network interface card (NIC) can report received CSI
  - Up to 30 subcarriers



- Has become very popular technique for Wifi sensing – used in most projects

Sensing with CSI

- CSI amplitude is a reliable metric for Wifi sensing
  - Consistent and repeatable, unique for different channel states
- CSI phase is much less reliable
  - Prone to errors such variation in Tx/Rx clock offset
  - Not always repeatable between trials
  - Some error correction techniques exist but not yet sufficient



Attempt to normalize CSI phase

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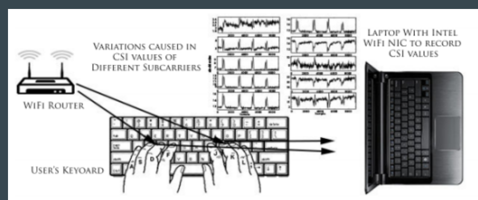
Keylogger Project

- 2017 project attempting keystroke recognition through Wifi signals
  - Also called WiKey
- Found that each keystroke generates a unique CSI time-series pattern



Keylogger: Sensing Mechanism

- Commercial MIMO WiFi receiver in laptop communicating with commercial MIMO router
  - Router in fixed position relative to laptop
- Combination of direct analysis and machine learning to evaluate keystokes
- Achieved 97..5% detection rate of keystrokes
- 96.4% recognition accuracy for classifying each key

Keylogger: Technical Details

- Keystroke time-series segmentation
  - Trend matching CSI-waveforms with observed waveforms
- Principal component extraction for different keys
  - Filter and apply DWT (Dynamic Time Warping) to individual keystroke CSI waveforms
- Keystroke feature comparison
  - DWT can evaluate distance between two shape feature

Keylogger: Limitations

- User had to sit still and type slowly in order to achieve 94% accuracy (1 stroke per second)
- Only works for particular distance and orientation of laptop and router – not generalized
- The project creators believe that with a large enough database, algorithm could be generalized to work anywhere

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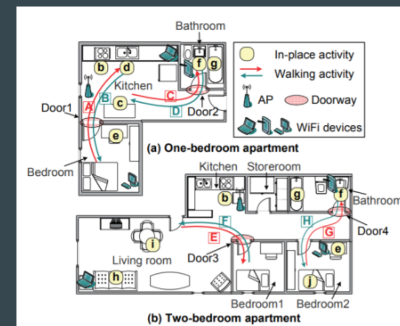
E-Eyes System

- 2014 project
- Focus on **Activity Recognition** as a series of movements that are either in-place or walking
- Uses CSI information as the basis of their analysis
- 92% TPR for one device
- 96% TPR for 3 devices with weighted voting ensemble method



E-Eyes: Data Processing

- **Data preprocessed**
  - Low pass filtering (DESF) for detection of only human interferences
  - MCS anomaly detection for removal of erratic CSI due to connection issues
- **Data segmented**
  - Moving variance threshold distinguishes between repetitive (in- place activity) or significant pattern changes (walking activity)

E-Eyes: SCoring Metrics

- **In-Place Metric**
  - Earth Mover's Distance metric for CSI 20 bin histogram
- **Walking Metric**
  - MD-DTW (Multiple Dimension Dynamic Time Warping) for similarity metric of walking CSI profiles that adjusts for speed changes

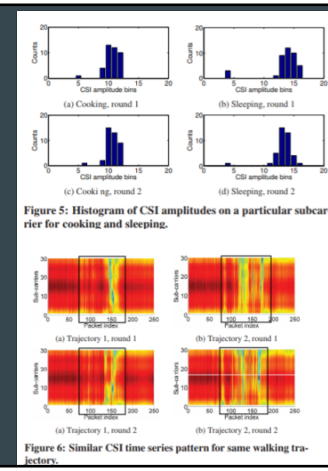


Figure 5: Histogram of CSI amplitudes on a particular subcarrier for cooking and sleeping.

Figure 6: Similar CSI time series pattern for same walking trajectory.

E-Eyes: Activity Recognition

- **Activity Identification**
  - Best scoring metric assigns CSI input to CSI profile
- **Adaptive System**
  - MAD (Median Absolute Deviation) technique identifies outliers that represent new profiles i.e. new activities not in the system
  - Entirely new system profiles can be generated when the layout of the room changes - detected using K-Means clustering of EMD

E-Eyes: Performance

- **Mesh Network**
  - By taking advantage of multiple connected devices in a room can improve TPR to 96%
  - Ensemble method such that each device makes a weighted vote on the classification

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Deep Learning System

- 2017 project uses Long-Short Term Recurrent Neural Network to classify activities by analyzing CSI signal

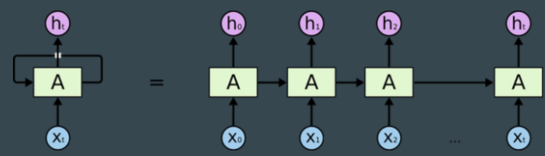
(c) Long Short Term Memory

Predicted

Actual	Lay down	Fall	Walk	Run	Sit down	Stand up
Lay down	0.95	0.01	0.01	0.01	0.00	0.02
Fall	0.01	0.94	0.05	0.00	0.00	0.00
Walk	0.00	0.01	0.93	0.04	0.01	0.01
Run	0.00	0.00	0.02	0.97	0.01	0.00
Sit down	0.03	0.01	0.05	0.02	0.81	0.07
Stand up	0.01	0.00	0.03	0.05	0.07	0.83

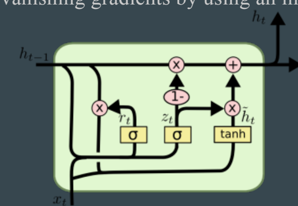
Deep Learning: RNN

- Recurrent Neural Networks capture time series nature of data to perform classification or regression



Deep Learning: LSTM

- Long-Short Term Memory networks are a specific kind of RNN that prevent vanishing gradients by using an input, output, and forget gate



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Deep Learning: Preprocessing

- Using 90 subcarriers CSI amplitude there was NO preprocessing of data
- Many existing methods use feature extraction from STFT or 2nd PCA component fed into HMM,SVM
- 2 second window for activity recognition

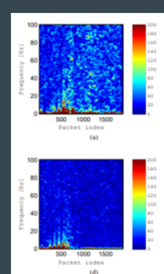
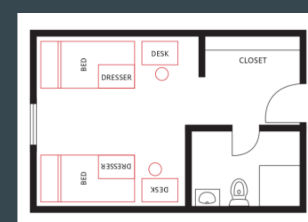


Fig. 4: The spectrogram of one subcarrier

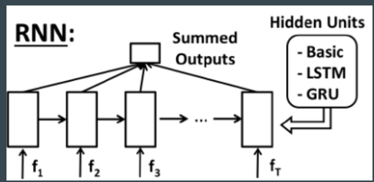
Deep Learning: Experiment

- 3 meters apart LOS, 1kHHz sampling
- Very promising method, but model must be trained for specific environment - sensitive to room layout changes



Deep Learning: Model Architecture

- LSTM model had
  - 90 subcarrier magnitude input
  - 200 hidden LSTM units - .2 second window
  - SGD training, 200 batch size



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Future Developments

- Further, deeper analysis of CSI can enhance current Wifi sensing techniques
  - More subcarriers and antennas can be utilized
  - If phase can be fully corrected from CFO/SFO, machine learning data effectively doubles
- More complex neural networks and deep learning techniques can be implemented
- Large data sets could lead to generalized gesture recognition algorithms
  - Not limited to experiment participants

Thank You

Questions?