# Wifi CSI data interpretation – Phase

## Leveraging the Phase Component of Wi-Fi CSI for Machine Learning and Environmental Sensing

the use of WiFi CSI (Channel State Information), focusing particularly on its phase component and exploring its wide-ranging applications in machine learning. WiFi CSI involves transmitting a signal into a room and monitoring how it is received at various locations. These signals capture environmental characteristics, and their variations can reveal dynamic objects such as the presence, movement, or activity of individuals. This capability enables Wi-Fi CSI to drive innovative applications such as precise localization, human activity recognition, and environmental sensing.

# Advanced Applications of Wi-Fi CSI:

### Localization:

The localization using Wi-Fi CSI relies on the propagation characteristics of radio waves to determine a person's position within a room with remarkable accuracy. By analysing signal strength variations and phase information from multiple antennas, such as those in a three-receiver configuration, triangulation of position becomes feasible. Each antenna receives radio waves altered by obstacles, movements, and environmental properties. The data, which includes amplitude and phase variations, provides spatial information about objects or individuals causing disruptions. Advanced techniques like phase difference of arrival (PDOA) and time difference of arrival (TDOA) are used to pinpoint exact locations by measuring phase or time shifts as signals arrive at different antennas. These insights are further enhanced through machine learning models trained to interpret spatial patterns, enabling real-time location tracking that is both precise and scalable.

### Activity recognition:

WiFi CSI also has profound implications for human activity recognition. Different activities uniquely affect the propagation of radio waves. For instance, walking creates periodic disruptions as the body repeatedly crosses the line of sight between the transmitter and receiver, whereas sitting produces a stable but distinct signal change. Machine learning algorithms can classify these patterns by training on datasets that record multiple instances of human activities and their corresponding signal variations. These trained models can then identify activities in real time, opening up applications in intelligent systems and non-intrusive health monitoring. For example, specific gestures or movements indicative of health issues can be detected promptly, providing valuable tools for eldercare and remote health monitoring solutions.

### What does Phase represent:

The phase component of Wi-Fi CSI is particularly valuable as it captures the timing of signals upon reaching the receiver. This timing reflects how signals are altered by the environment, such as through reflections, diffractions, or obstructions. Phase information offers critical insights into signal integrity, directionality, and the environmental impact on signal propagation. When incorporated as a feature in machine learning models, phase data significantly enhances predictive accuracy. Feature extraction from the complex numbers representing CSI data can be accomplished in several ways. The real and imaginary parts can be treated as separate features to preserve their distinct information, or the data can be transformed into polar coordinates, making the phase explicitly usable. Preprocessing techniques, such as phase unwrapping and sinusoidal encoding, address phase data's inherent non-linearity and discontinuities, ensuring it is optimized for machine learning models. Sinusoidal encoding is particularly effective, smoothing out data inconsistencies and enhancing its usability in predictive systems.

## WiFi CSI and Phase Data:

## A Framework for Machine Learning and Intelligent Systems

### Feature Extraction from complex numbers:

The potential applications of Wi-Fi CSI extend beyond localization and activity recognition. Its ability to sense environmental changes can be leveraged in anomaly detection systems, where deviations in signal patterns indicate unusual events such as intrusions or accidents. In smart homes, Wi-Fi CSI can enable devices to respond intelligently to user presence and activities, creating more interactive and adaptive environments. In industrial settings, it can monitor machinery or personnel movements, enhancing workplace safety and efficiency. Furthermore, Wi-Fi CSI data could revolutionize human-computer interaction, enabling gesture-based control systems that require no additional hardware.

### Exploring the Phase Component of Wi-Fi CSI in Localization and Activity Recognition

Not only underscores the versatility of Wi-Fi CSI but also provides a framework for integrating its phase component into advanced machine learning applications. The findings demonstrate how preprocessing techniques and feature engineering can unlock the full potential of phase data, paving the way for future innovations in non-intrusive sensing and intelligent system design. From precise localization to advanced health monitoring, Wi-Fi CSI—and its phase data—opens doors to smarter, more responsive environments and systems that adapt seamlessly to human needs.

**Sinusoidal Encoding:**

Sinusoidal encoding should be used as it is well-suited for this type of data. It makes it easier for the data to be used in machine learning models by ignoring the discontinuations in the data due to how the phase data is likely to appear.

Info about machine learning networks and CSI data: https://www.mdpi.com/2079-9292/12/18/3935