



# SGRS: A Sequential Gesture Recognition System using COTS RFID

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# 1

PART ONE

## Motivation



# Gesture Recognition Applications



**Motion gaming**



**Smart home**



**VR or AR controller**



**Sign language**



# Gesture Recognition Technologies



## Computer Vision

- Line of Sight
- Sensitive to light conditions
- Privacy concerns



## Wearable Sensor

- Inconvenient
- Poor scalability



## Device-free RF

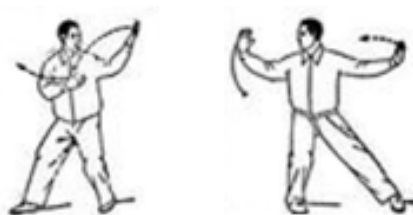
- Cannot differentiate multiple parts

**Hard to identify sequential gestures**

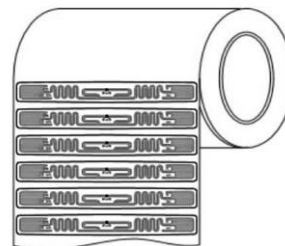


# Sequential Gesture Recognition System

- Identify **sequential gestures**, which are composed of a series of temporally-related simple actions in order.



- A sequential gesture recognition system with **COTS RFID** devices.
  - Battery-free
  - Scalable
  - Non-specific





# Sequential Gesture Recognition System

- **Experiment subjects**

Traffic command gestures of Chinese traffic police



**stop**



**change lane**



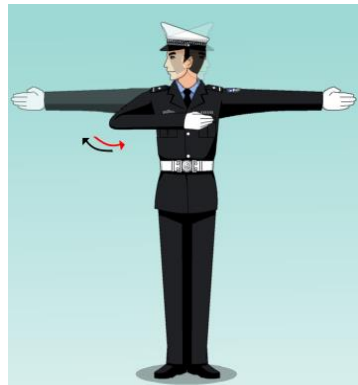
**left turn pending**



**slow down**



**pull over**



**go straight**



**turn left**

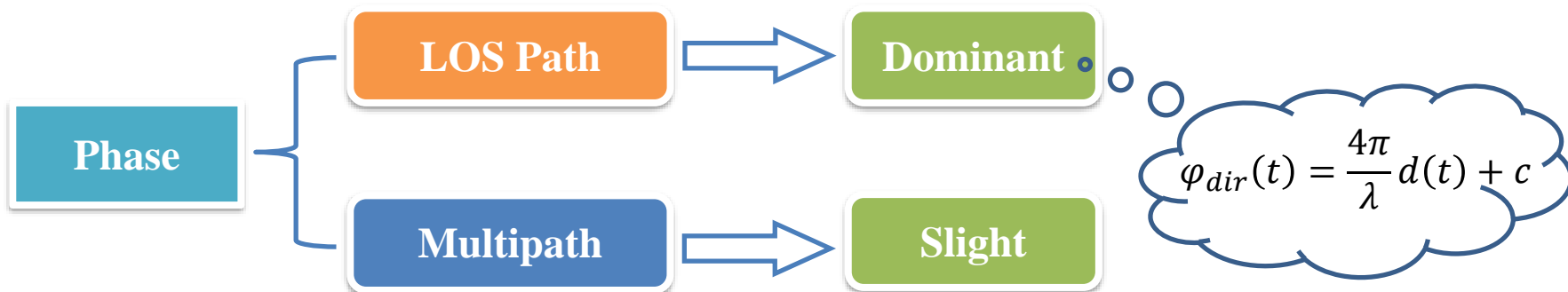


**turn right**

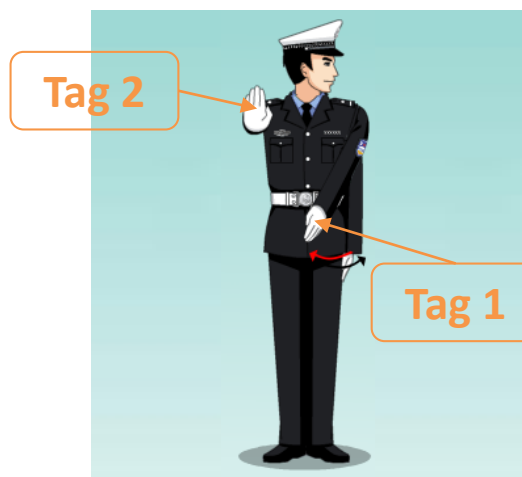


# Key Insight

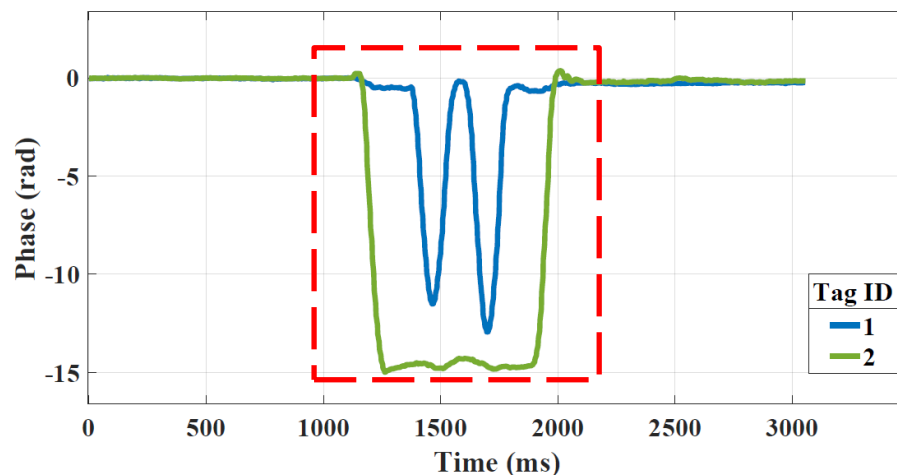
- RFID phase is affected slightly by the multipath but dominated by the time-varying distance between the tag and the antenna.



- Fine-grained signal phase is capable of perceiving sequential gestures.



turn left





# 2

## PART TWO

# Challenges



# Challenges and Solutions

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**C1**

## **Describe temporally-related actions of sequential gesture**

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- The temporal relation of the same body part
- Combined expression of different body parts

## **Extract features for each time window**

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- Extract time-frequency domain features for each tag in each sliding window
- Combine the features of multiple tags into a feature vector

**S1**



# Challenges and Solutions

C2

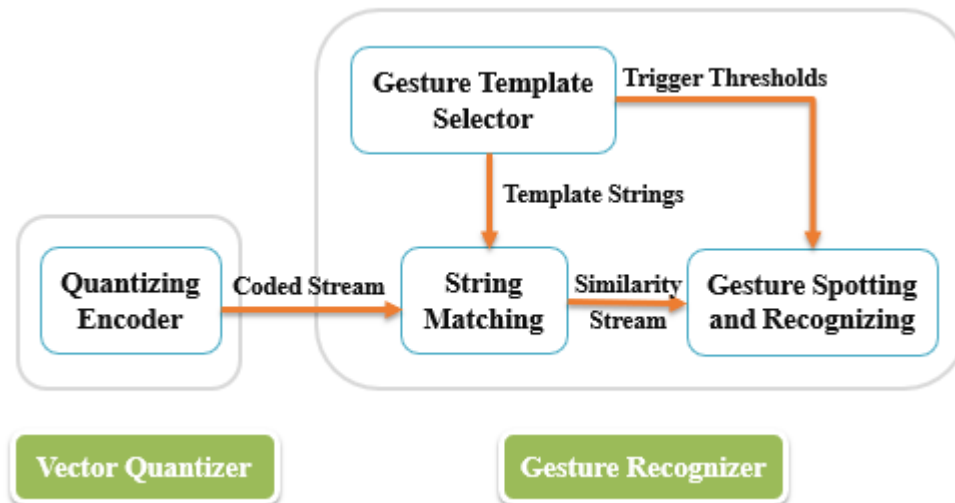
## Fast and precise recognition

- Important for an instant human-computer interaction interface

## Vector quantization and string matching

S2

- Vector quantization for mapping the high-dimensional feature vectors into a discrete subspace of lower dimension
- Fast and efficient string matching algorithm for recognition



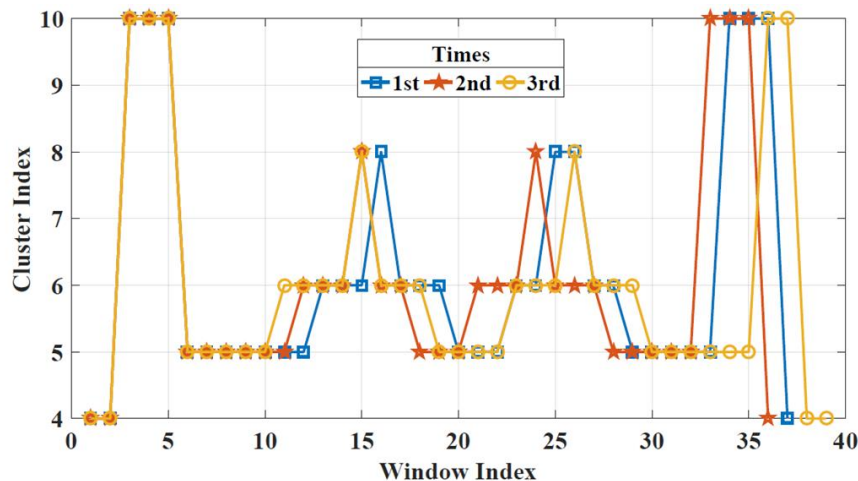


# Challenges and Solutions

C3

## Individual diversity

- Users with different gesture durations
- Not identical even for the same person



## Improved edit distance

- Improved edit distance algorithm for identifying gestures and suppressing individual diversity
- Increase intra-class similarity and reduce inter-class similarity

S3

# 3

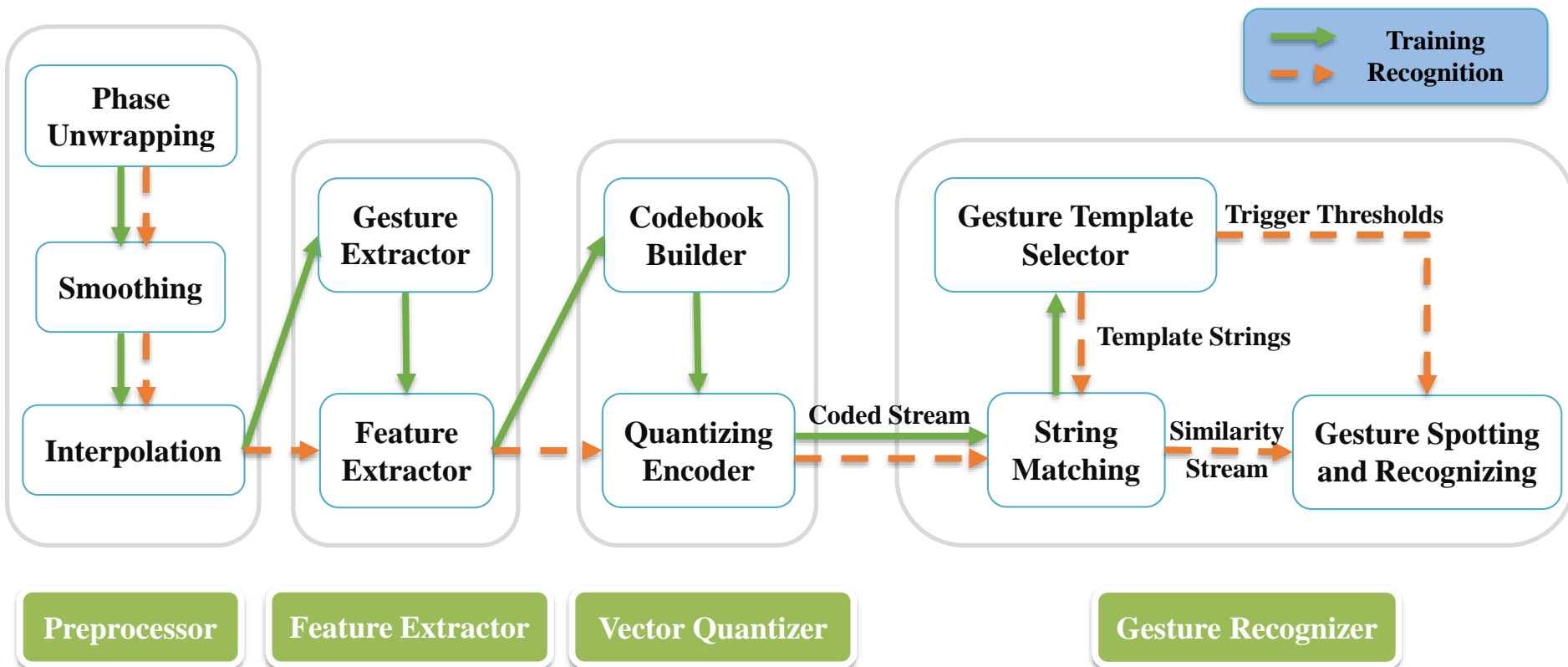
## PART THREE

# System Architecture



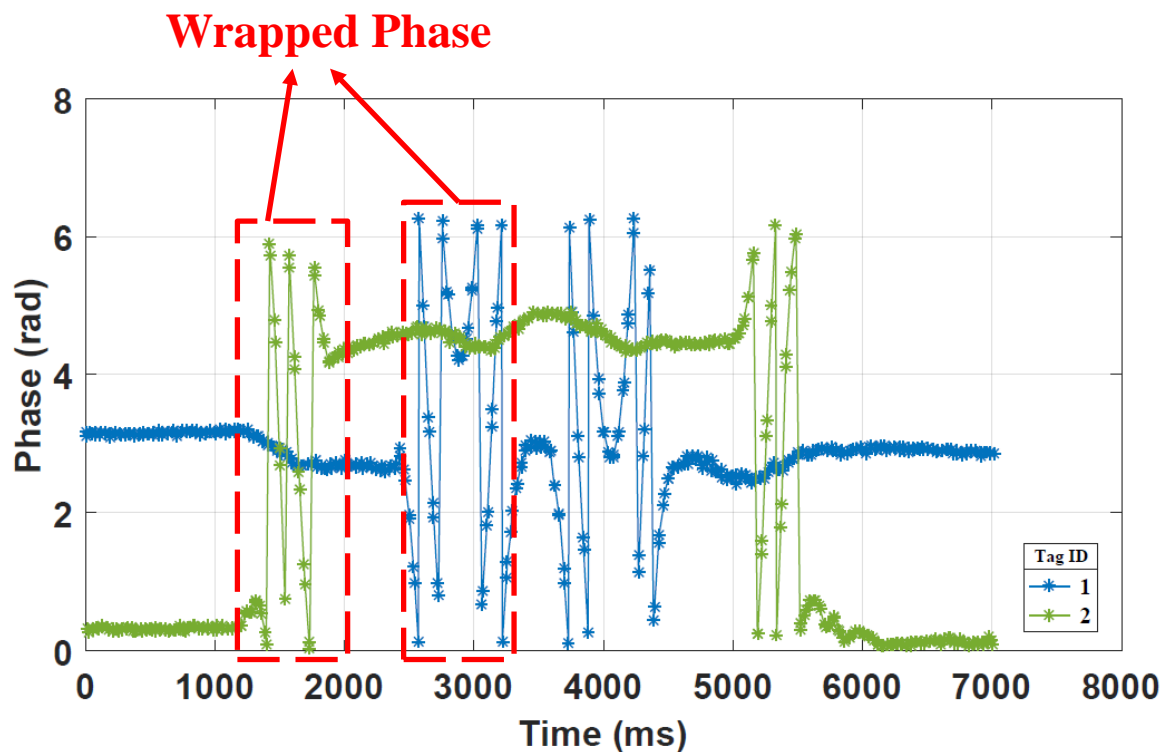
# System Overview

## SGRS: Sequential Gesture Recognition System





# Preprocessor

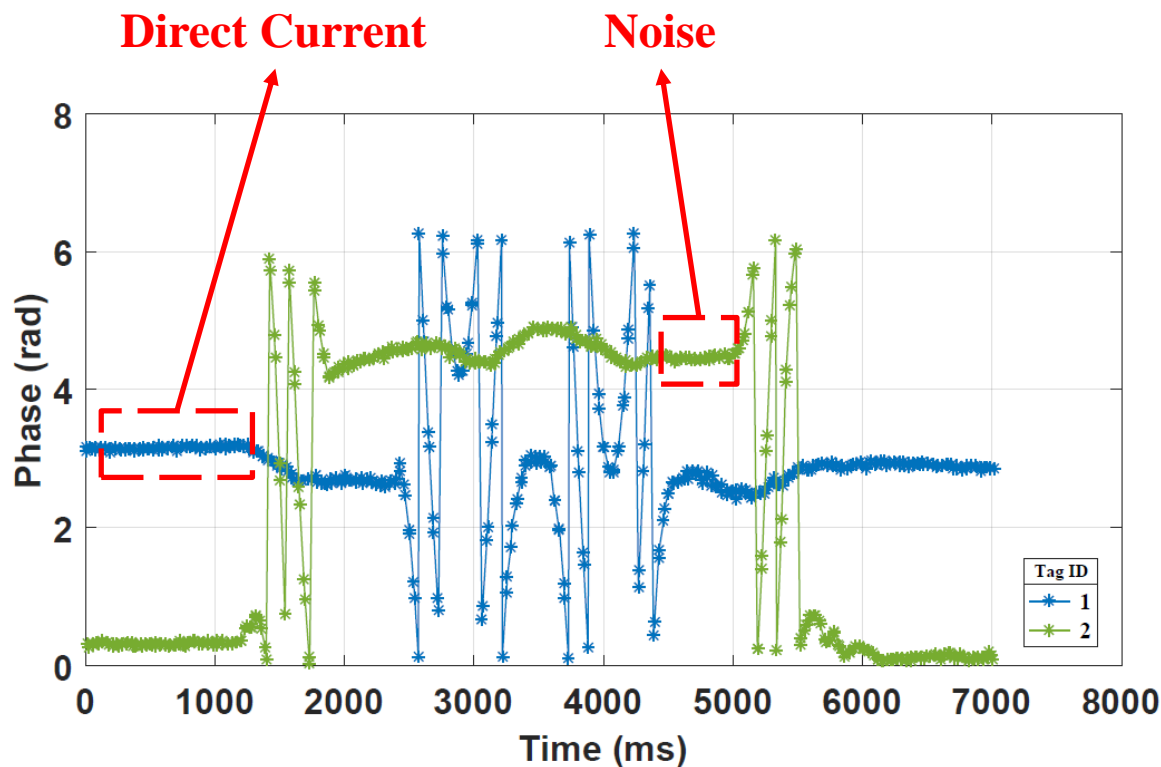


## Phase unwrapping

$$p_i = \begin{cases} p_i - 2 * \pi, & p_i - p_{i-1} \geq \pi \\ p_i, & |p_i - p_{i-1}| < \pi \\ p_i + 2 * \pi, & p_i - p_{i-1} \leq -\pi \end{cases}$$



# Preprocessor



Phase unwrapping

$$p_i = \begin{cases} p_i - 2 * \pi, & p_i - p_{i-1} \geq \pi \\ p_i, & |p_i - p_{i-1}| < \pi \\ p_i + 2 * \pi, & p_i - p_{i-1} \leq -\pi \end{cases}$$

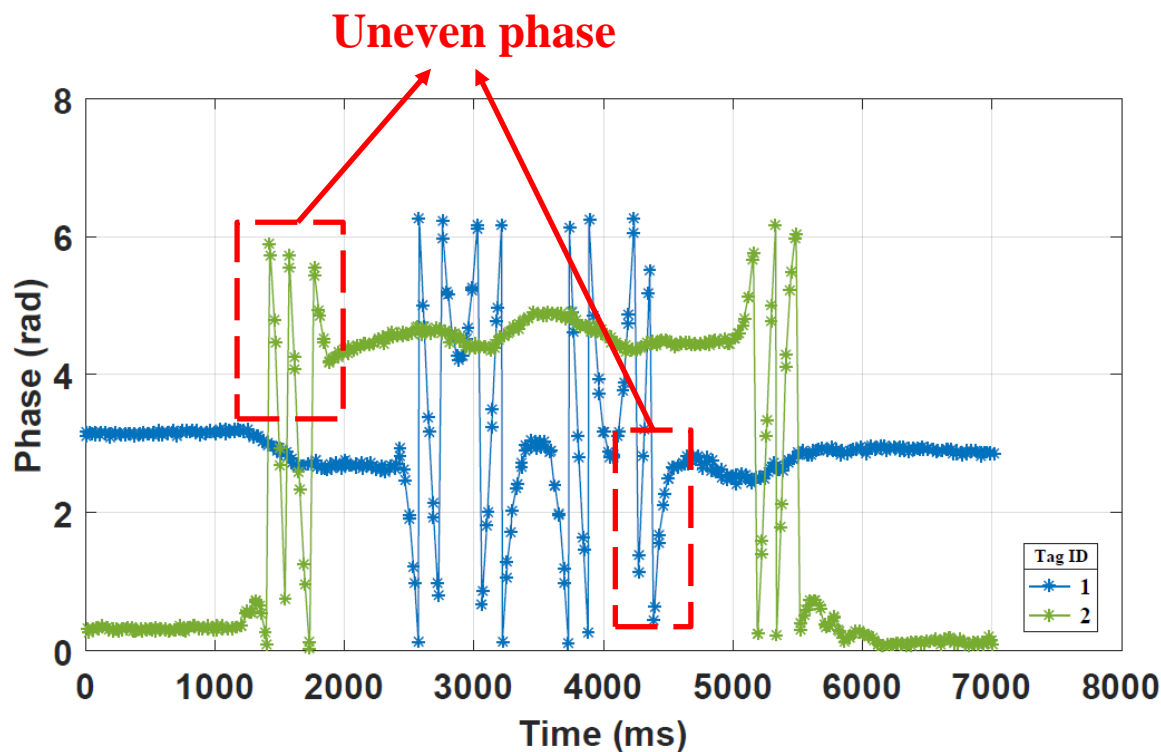
Smoothing

Hampel identifier  
Weighted moving average filter  
DC removal





# Preprocessor



Phase unwrapping

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Smoothing

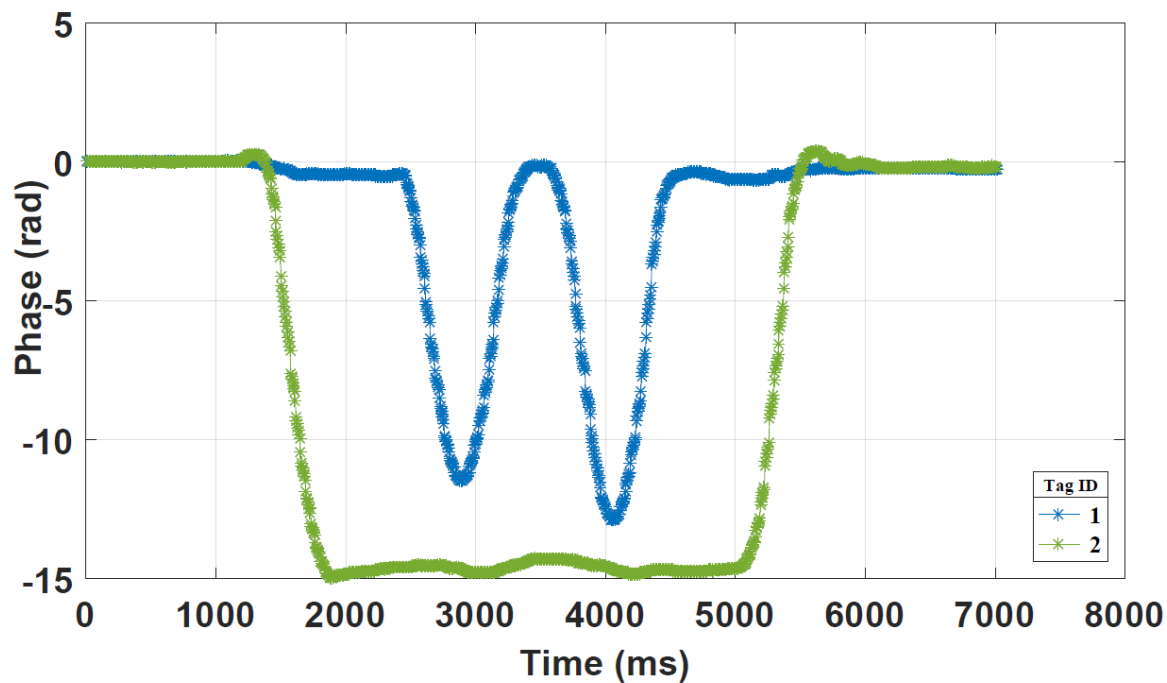
Hampel identifier  
Weighted moving average filter  
DC removal

Interpolation

Linear interpolation



# Preprocessor



Phase unwrapping

$$p_i = \begin{cases} p_i - 2 * \pi, & p_i - p_{i-1} \geq \pi \\ p_i, & |p_i - p_{i-1}| < \pi \\ p_i + 2 * \pi, & p_i - p_{i-1} \leq -\pi \end{cases}$$

Smoothing

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DC removal

Interpolation

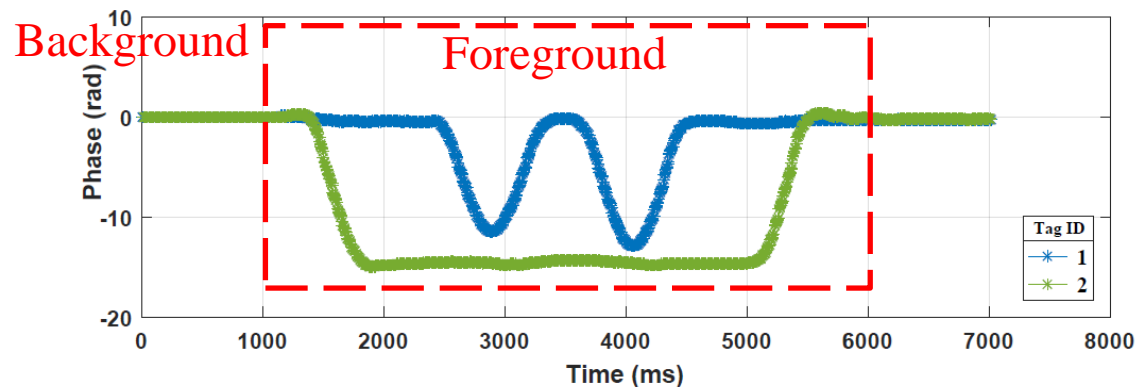
Linear interpolation



# Feature Extractor

- **Gesture Extraction (offline training)**

Before feature extraction, the signal fragment corresponding to the gesture is extracted by Foreground detection method.



- **Feature Extraction**

For each sliding window, extract **time-frequency domain features** of each tag's phase signal into a feature vector.

Feature	Description
Mean	Average phase
Standard deviation	Phase fluctuation
Peak-to-peak amplitude	Magnitude of phase discretization
Standard deviation of PSD	Energy strength fluctuation



# Vector Quantizer

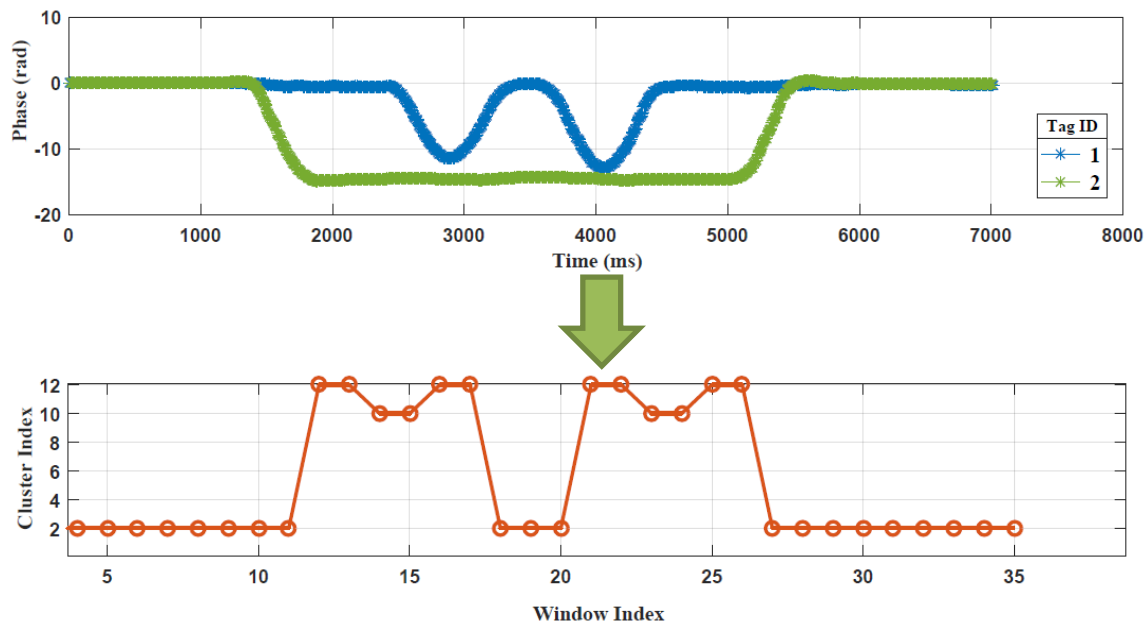
- **Codebook Builder (offline training)**

Cluster the feature vectors by **k-means** algorithm and use the category number (cluster index)  $i$ , centroid vector  $c_i$ , mean  $\mu_i$  and standard deviation  $\sigma_i$  as an item in the codebook.

$$\langle i, c_i, \mu_i, \sigma_i \rangle$$

- **Quantizing Encoder**

The feature vectors of a series of windows are encoded into a coded stream according to the codebook.



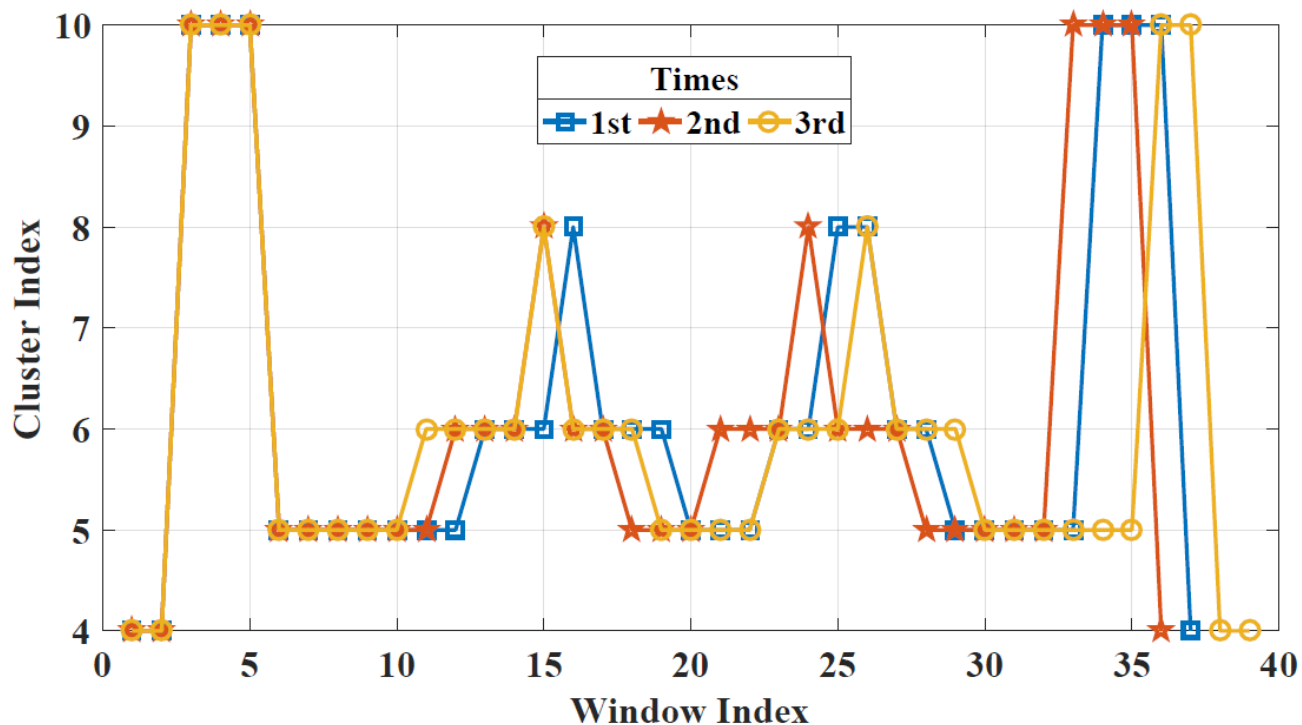


# Gesture Recognizer

## ● Edit Distance

Calculate the distance between two strings in terms of the minimum number of edit operations (insertion, deletion and substitution) needed for transforming one to another.

$$D(i, j) = \min[D(i-1, j) + p, D(i, j-1) + q, D(i-1, j-1) + r]$$





# Gesture Recognizer

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## ● Improved Edit Distance

1. Reduce the cost of edit operations to  $e$  ( $e < 1$ ) when the current symbol is the same as the previous one.
2. The similarity between  $S_1$  and  $S_2$  :

$$T(S_1, S_2) = 1 - \frac{D(m, n) + C(m, n)}{\max(m, n)}$$

$$C(m, n) = m - \sum_{i=1}^m 1_{S_2}(S_1(i)) + n - \sum_{j=1}^n 1_{S_1}(S_2(j))$$

$$1_A(x) := \begin{cases} 1, & x \in A \\ 0, & x \notin A \end{cases}$$

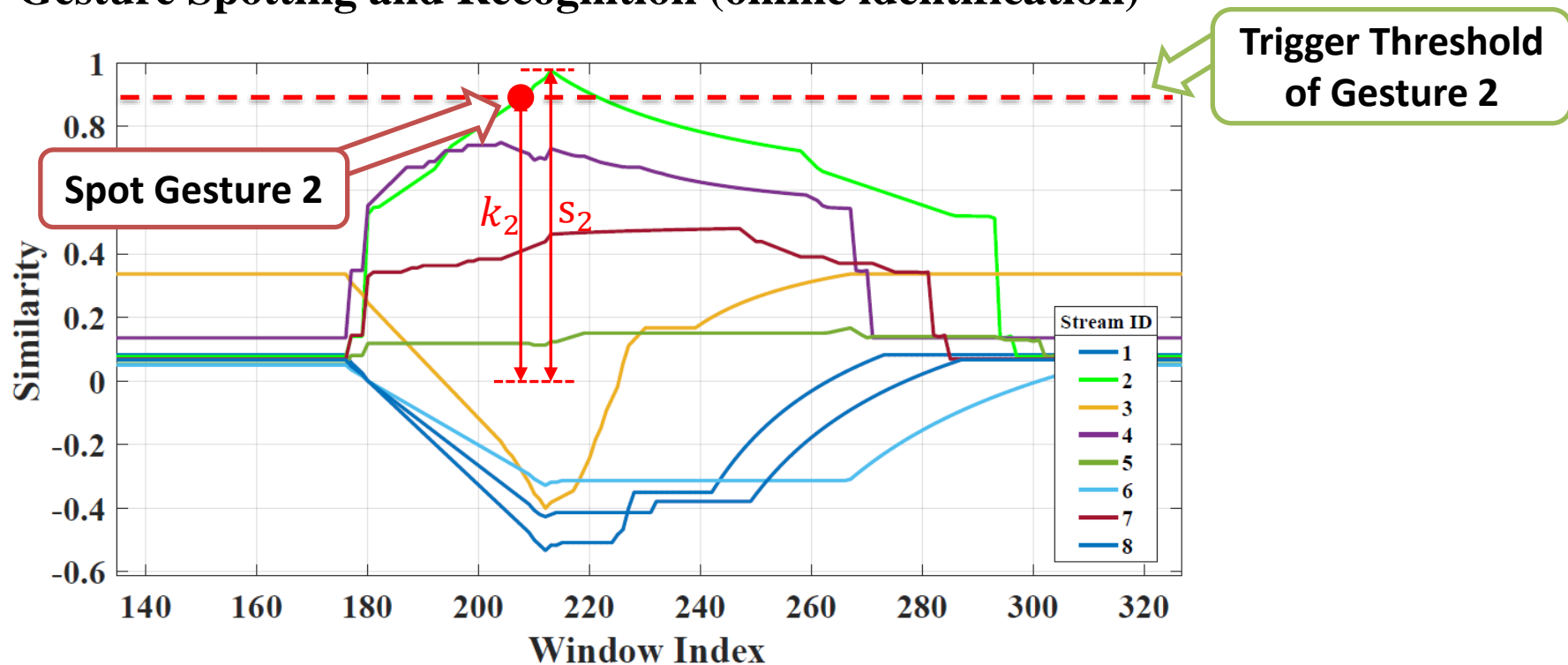


# Gesture Recognizer

- **Gesture Template Selector (offline training)**

Choose a template for each sequential gesture and generate the corresponding trigger threshold  $k_g$ .

- **Gesture Spotting and Recognition (online identification)**



When collision happens, select the **highest confidence level**  $cl_i = \frac{s_i}{k_i}$

# 4

## PART FOUR

# Implementation and Evaluation





# Implementation

- **Hardware**

ImpinJ R420 reader



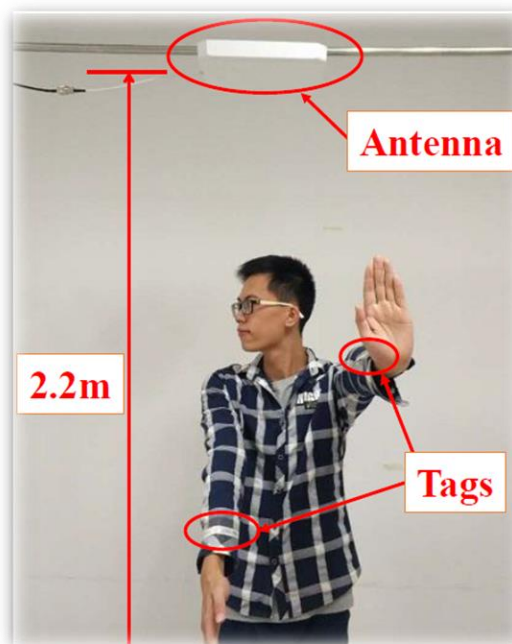
Alien AZ-9640 tags



Laird S9028PCR antenna



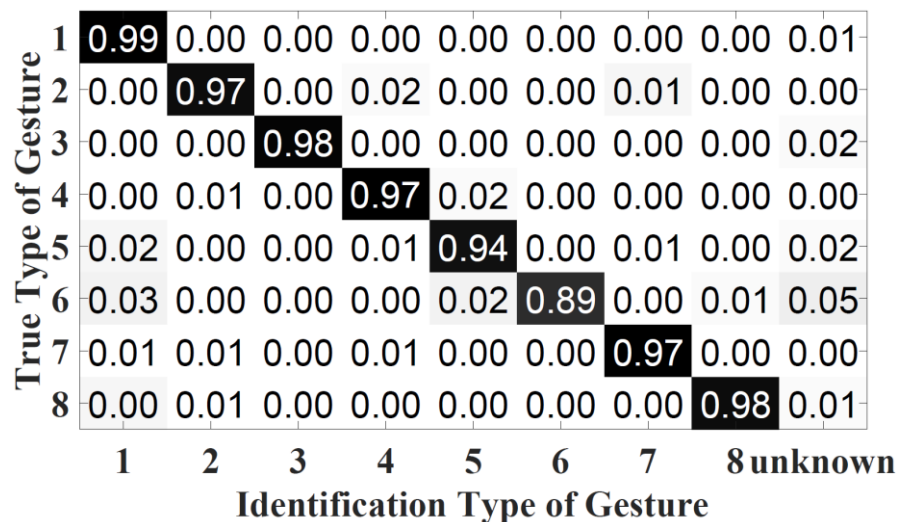
- **Setup**



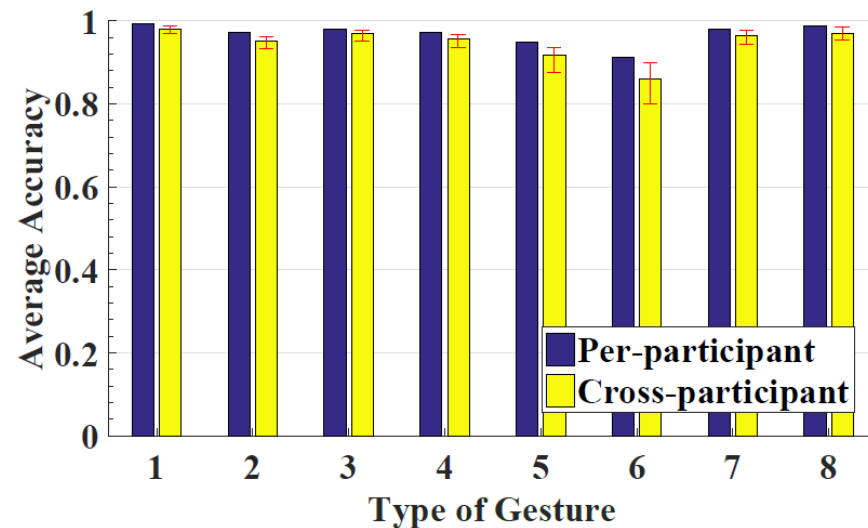


# Evaluation

## Recognition Accuracy Analysis



## Effect of Suppressing Individual Diversity

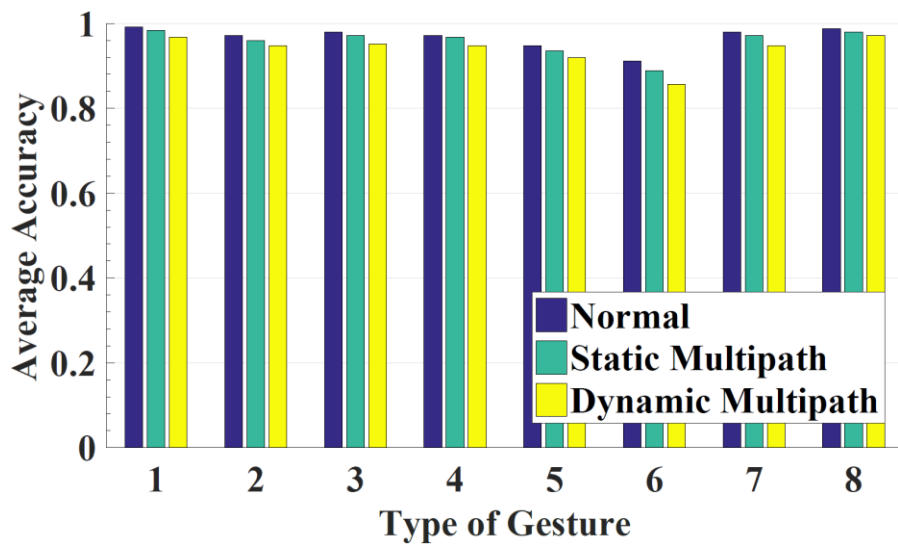


- The average recognition accuracy is 96.2%
- The accuracy of per-participant validation is 96.8%
- The accuracy of cross-participant validation is 94.6%

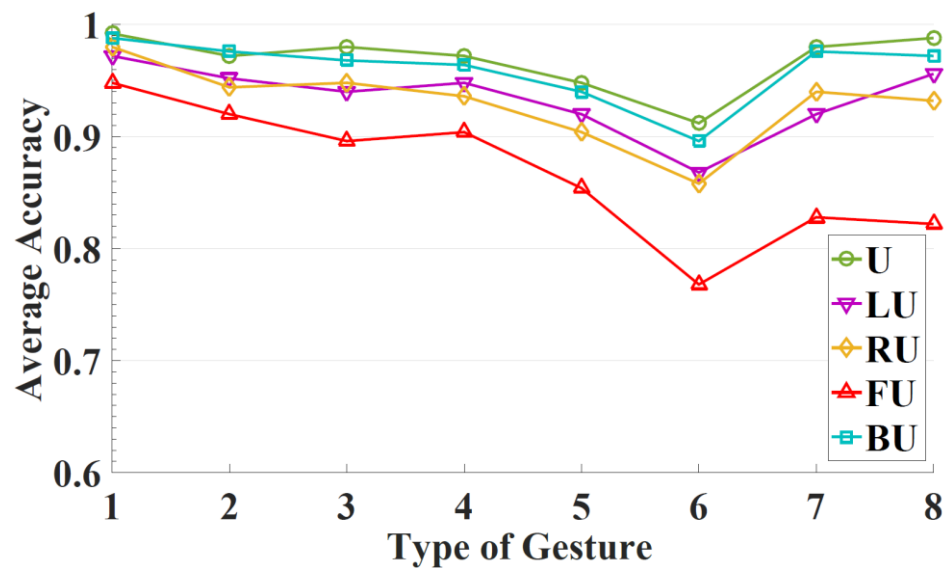


# Evaluation

## Effect of Resisting Multipath



## Effect of Diverse Positions





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PART FIVE

# Conclusion



# Conclusion

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- Propose the design, implementation and evaluation of **SGRS**, a sequential gesture recognition system
  - Leverage the RFID phase information to perceive the sequential gesture
  - Incorporate the vector quantization and improved edit distance to identify sequential gesture
- Implemented purely based on **COTS RFID** devices
- Achieve an average recognition accuracy of 96.2% and demonstrate the **robustness** and **feasibility** of SGRS

# Q & A



**SGRS: A Sequential Gesture Recognition System  
using COTS RFID**



# K-means

