University of Pittsburgh

SlowMo – Enhancing Mobile Gesture-Based Authentication Schemes via Sampling Rate Optimization

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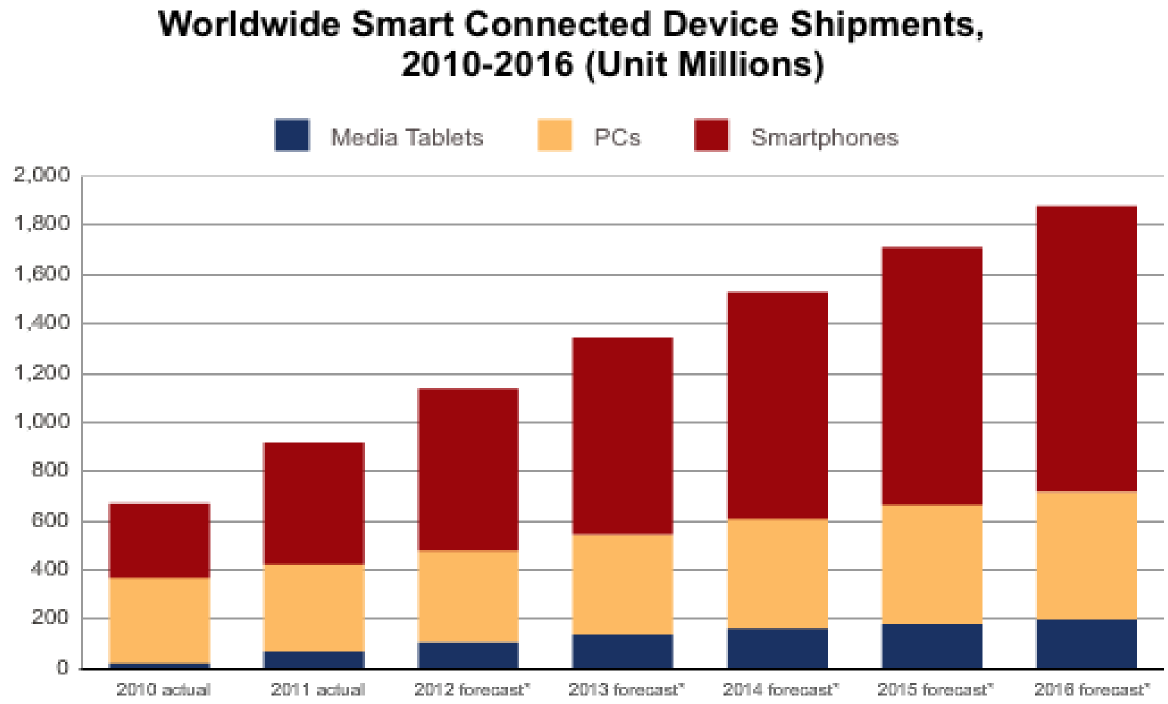
Outline

- Current State of Mobile Security
- Our Gesture-Based Mobile Security Solution
- Data Capture and Pre-Processing
- Results and Analysis
- Conclusion

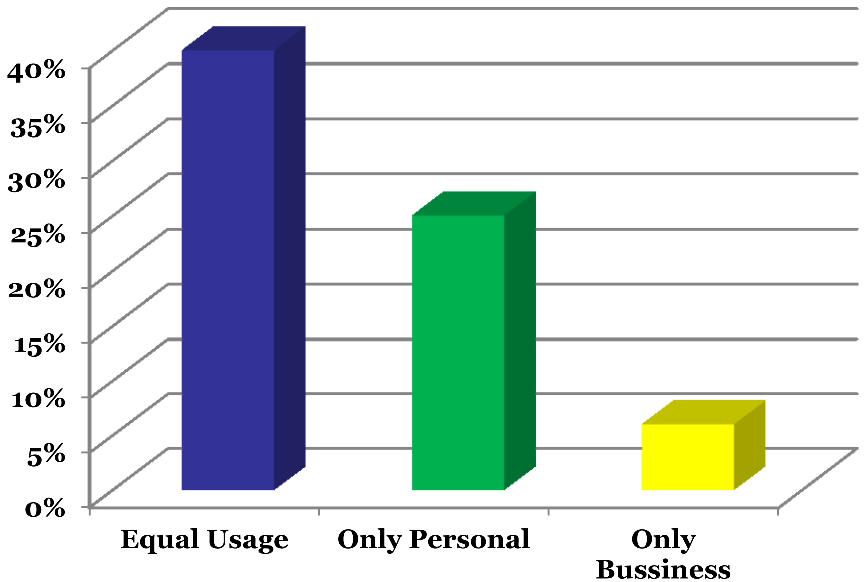
Proliferating Devices

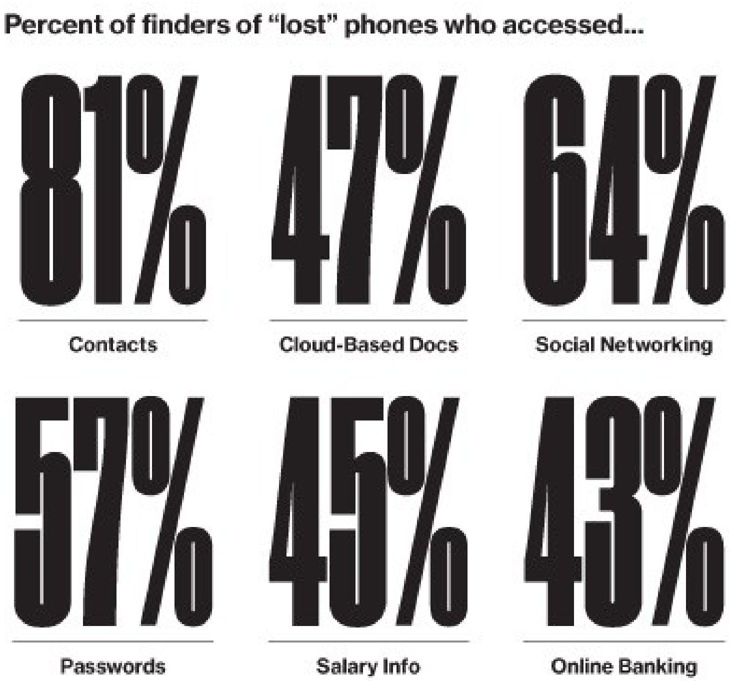
- **Over 26 billion smart connected devices before 2020**
- **Many household objects embedded with electronics and sensors**



Data Stored On Smart Devices

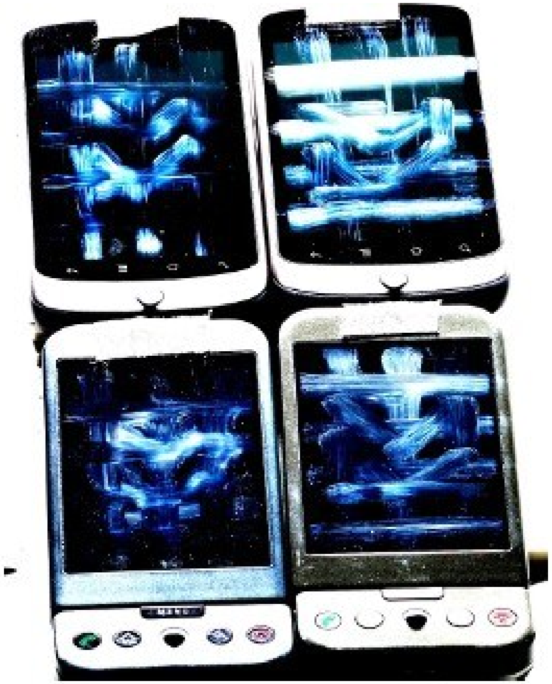
- 2/3 of people store a moderate or a significant amount of personal data on their smart mobile devices
- 1/3 of mobile phones are misplaced at least once a year





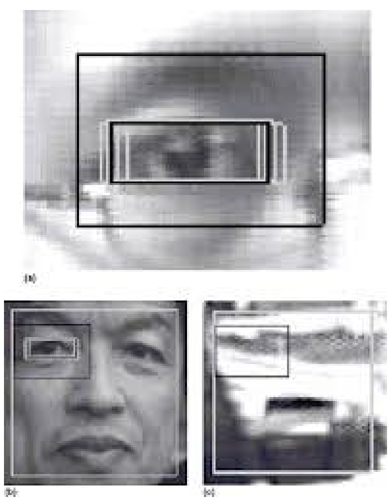
Existing Security Methods

- Robust security methods become of increasing importance
- Most popular schemes like PIN and pattern lock remain easily bypassed

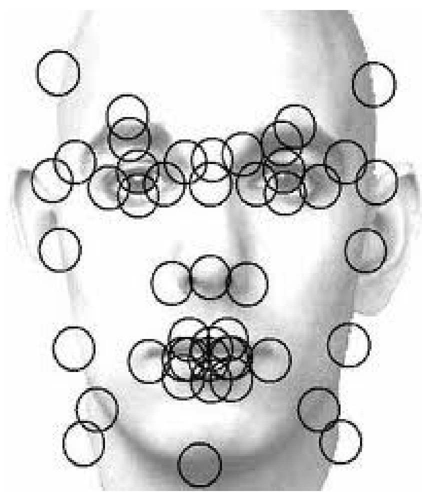


Existing Security Solutions

- Emerging trend is integration of fingerprint scanners
- Android devices allow for facial recognition
- Unique and difficult to reproduce, yet user can be forced to supply information



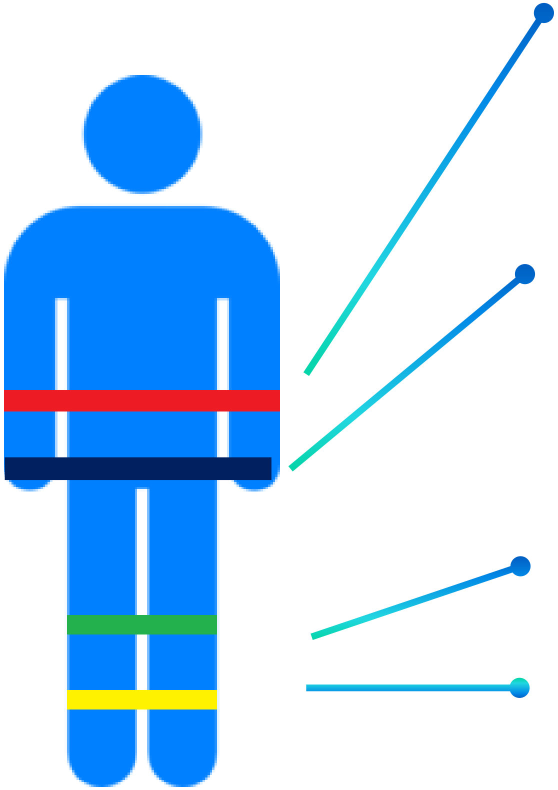
Iris



Facial

Finger Print

Smart Device Security



- **51%** have neither keypad locks nor passwords on their smartphone.
- **43%** of consumers consider security features of importance
- **19%** have passwords.
- **10%** have both keypad lock and passwords.

Ethological Security

- Use of user activity as a form of authentication
- Most promising is gesture-based security
  - The way in which a user interacts with a device as authentication

What’s In a Gesture

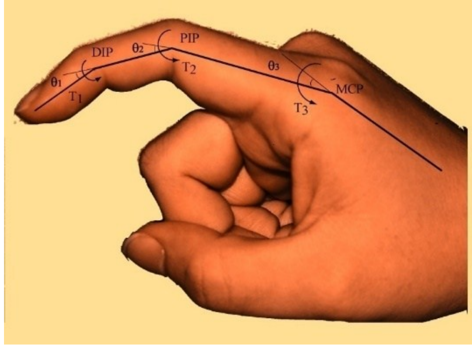
- “Gesture” is a repeatable, recordable pattern created when a user interacts normally with a device
- Examples: the way a user holds a device, how they interface with the screen, daily routines/activities

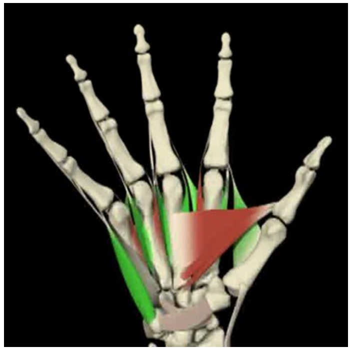
Benefits of Gesture-Based Security

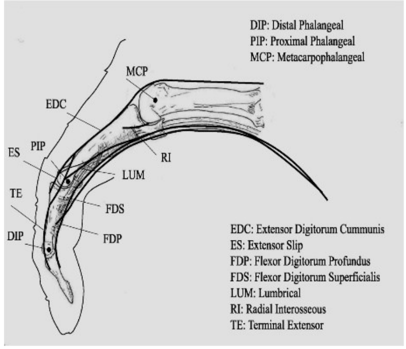
- Functions using only existing sensors
  - No new hardware, drivers, OS support, etc.
- Difficult to hack
  - Degrees of freedom are large and brute-force attacks are all but impossible
- Constantly changing identifier
  - Usage patterns slowly change over time
- Protects the user
  - Injuring the user could make the device useless to everyone

Is A Gesture Unique?

- In a word: yes
- Everyone has their own unique physical make up



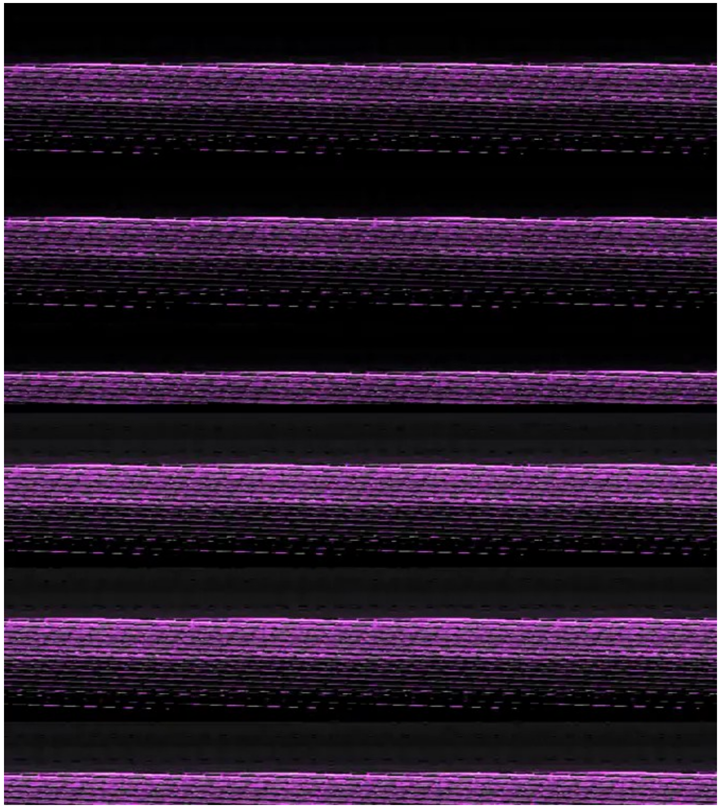




The hand alone has 29 pieces of bone, 123 pieces of ligament, 35 pieces of muscle, and 48 strips of nerves

Is A Gesture Unique?

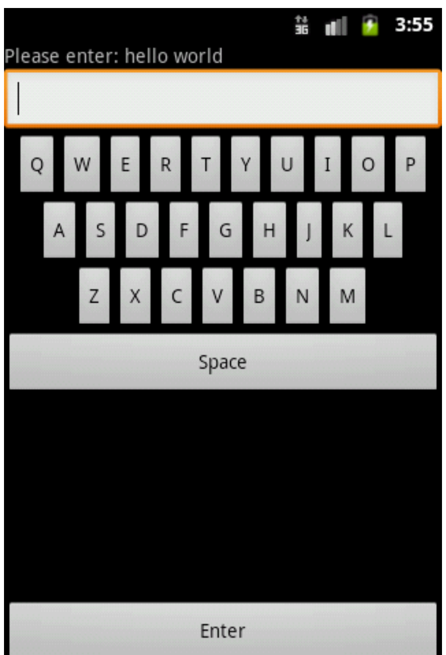
- **Everyone has a preferred way to interact with a device**

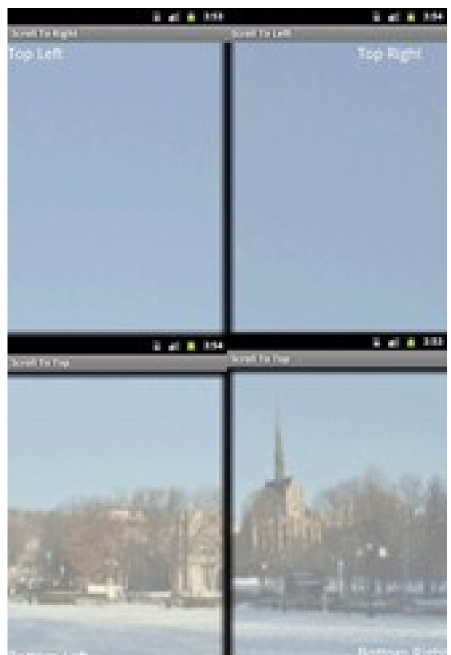


The video to the left shows two users entering the same PIN on the same phone. They were given no instructions other than to simply enter the code.

Are Gestures Repeated?

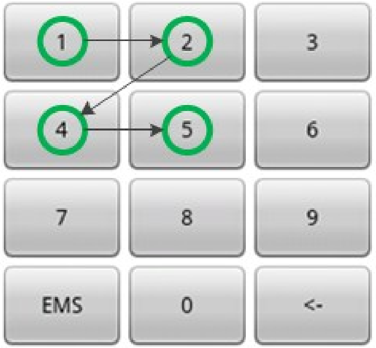
- **It is not enough that gestures are unique**
- **Must be repeatable**
- **Verify this experimentally**

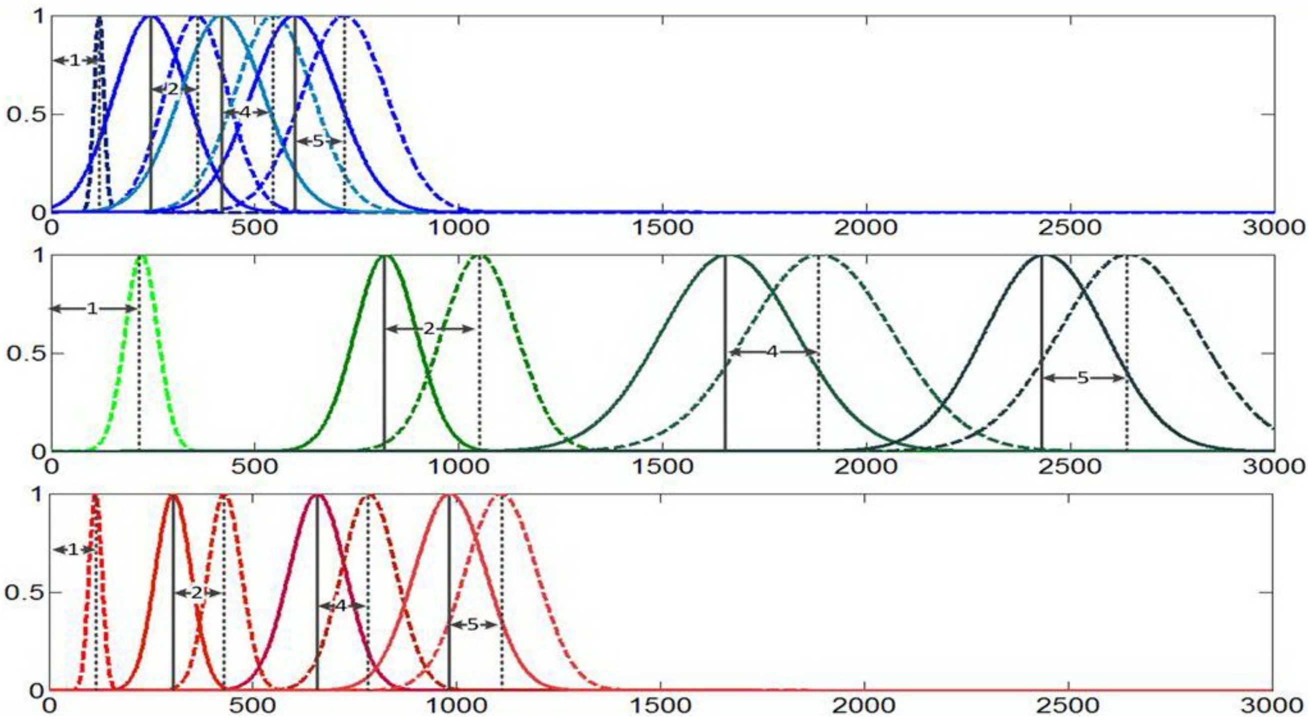




To the left are screenshots from within an Android app we created to record users' gestures. Shown are the test cases where the user is asked to enter a text message and when the user is asked to swipe.

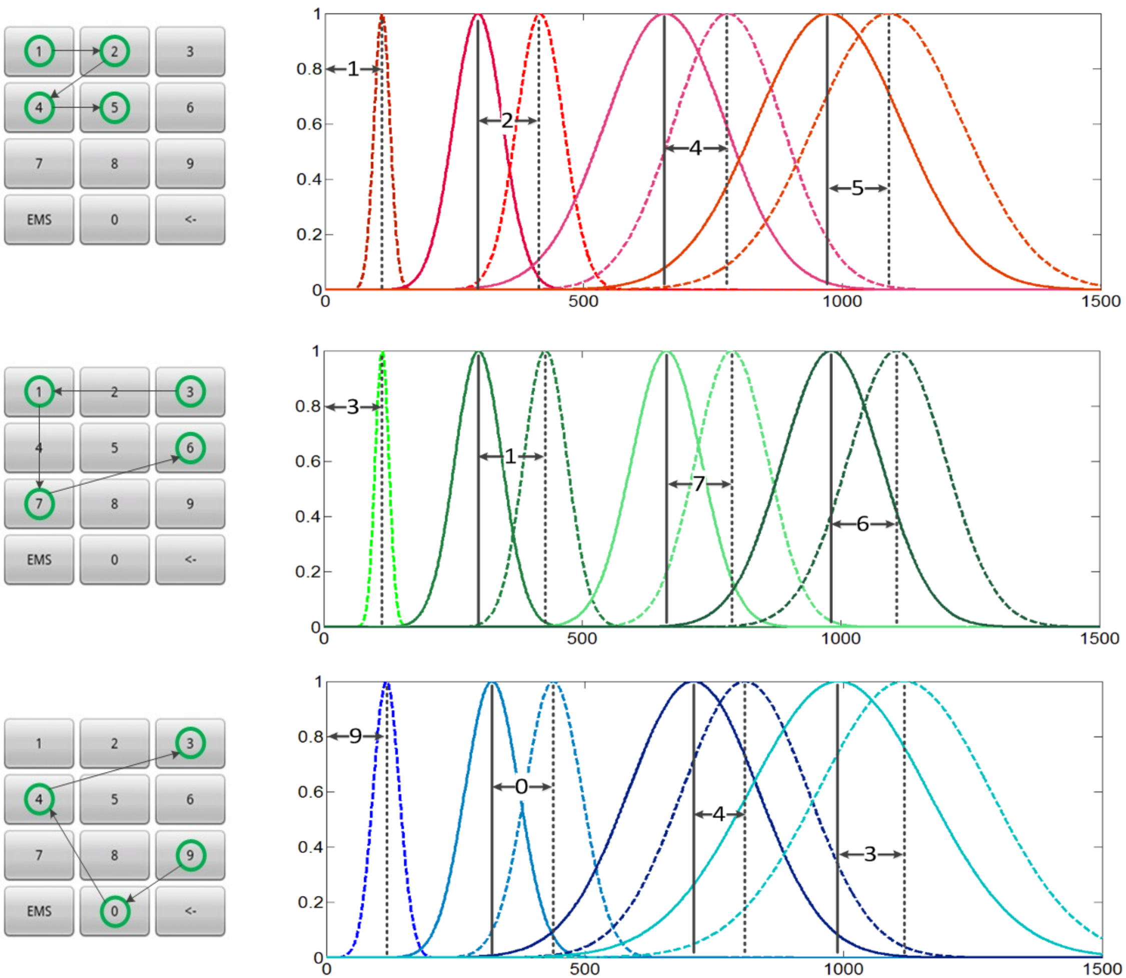
PIN Lock Integration





- **We compared three volunteers' Pressing Time Distributions (PTD) for the Password of 1245. Not only is the PTD unique per user, there is very little variation between samples.**

PIN Press Timing Distributions



- Across different PIN's, user PTD remains the same
- Indicates that at least some gesture features are constant for a single user

Further Analysis

- Significant difference between users
- Only small deviation across same user
- Verifies that gestures are unique and repeated

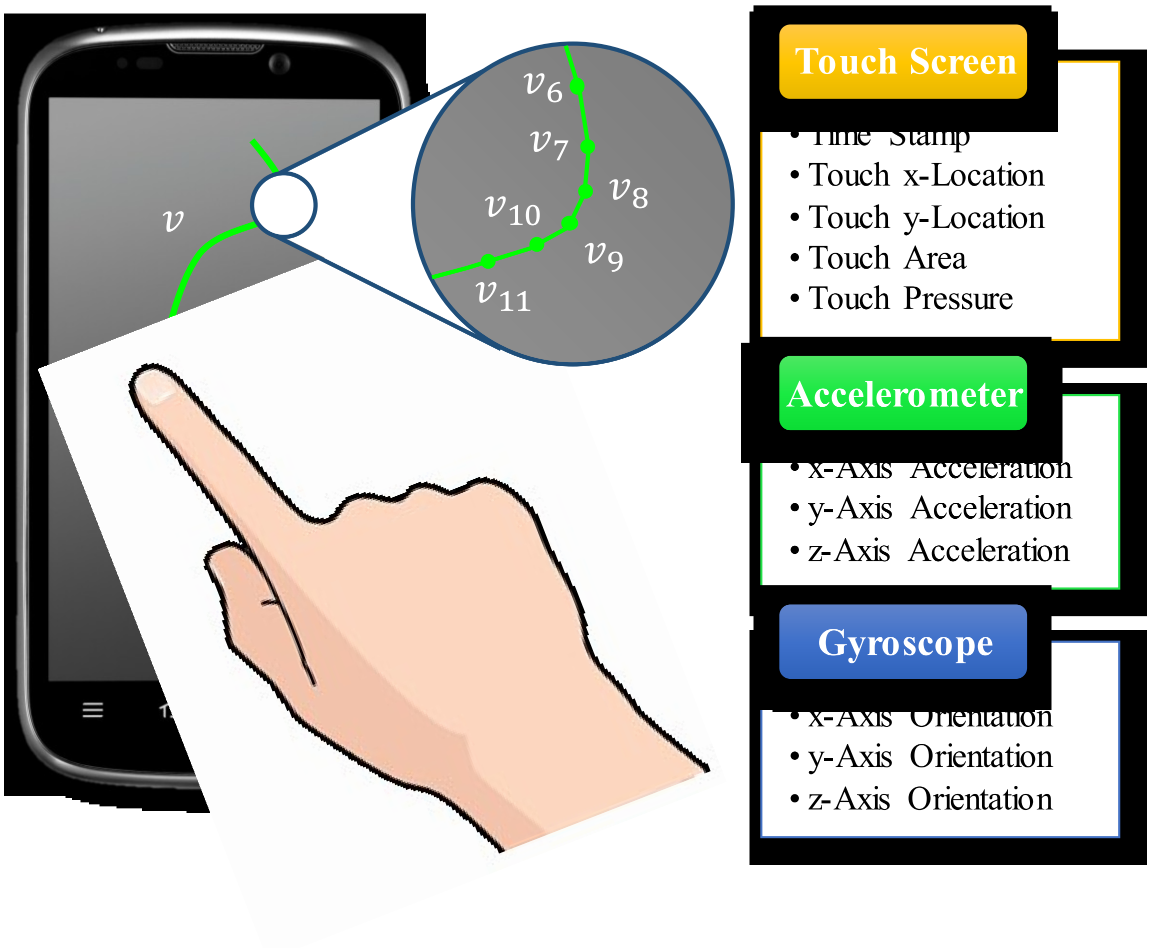
Avg. Contact Area	9043	1245	3179	Std. Deviation
Mid-Age Female	0.1707	0.1762	0.1715	0.0029
Young Female	0.1456	0.1541	0.1529	0.0046
Young Male	0.1977	0.2008	0.1998	0.0015
Standard Deviation	0.0212	0.0191	0.0192	

Avg. Pressure	9043	1245	3179	Std. Deviation
Mid-Age Female	0.5293	0.5561	0.5411	0.0134
Young Female	0.4611	0.5013	0.4910	0.0208
Young Male	0.5668	0.6100	0.5796	0.0222
Standard Deviation	0.0436	0.0443	0.0363	

How to Record Gestures

- The Android operating system allows access to all sensors on a device
- Includes GPS, magnetometer, barometer, light sensor, proximity sensor, touchscreen, accelerometer, gyroscope, and many more
- With data from all of these sensors, we can easily capture gesture data from a user

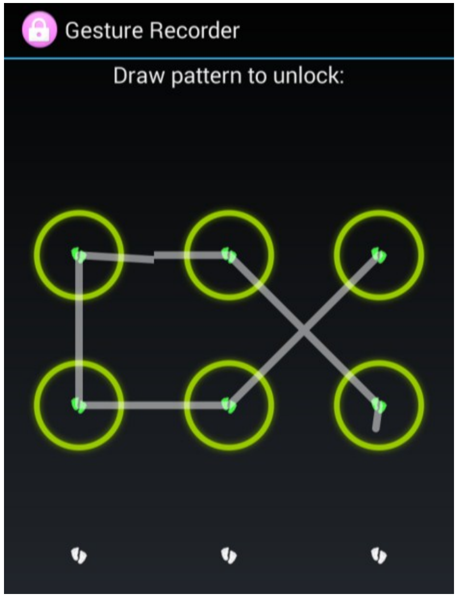
Representing Gesture

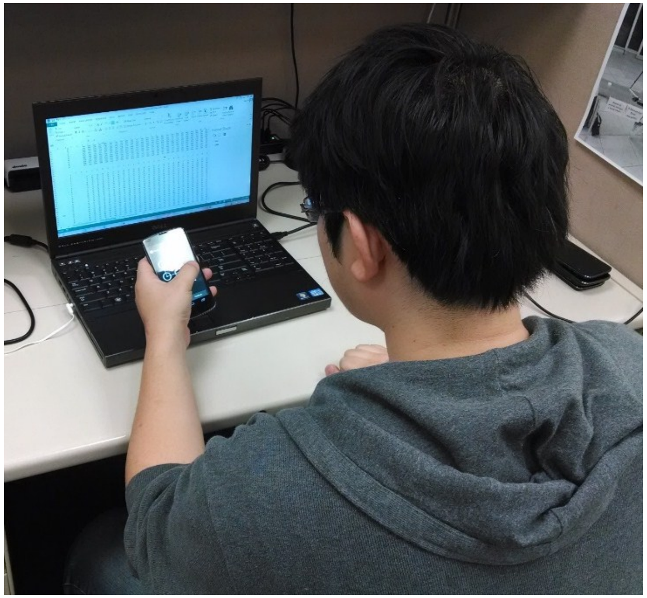


- **11 features across 3 sensors**
- **Single gesture can be visualized as a set of sample points**

Capturing Gesture

- Created an Android application that mimics the pattern lock
- Asked all users to enter the same pattern
  - Eliminates possibility of identifying user through differences in the patterns themselves



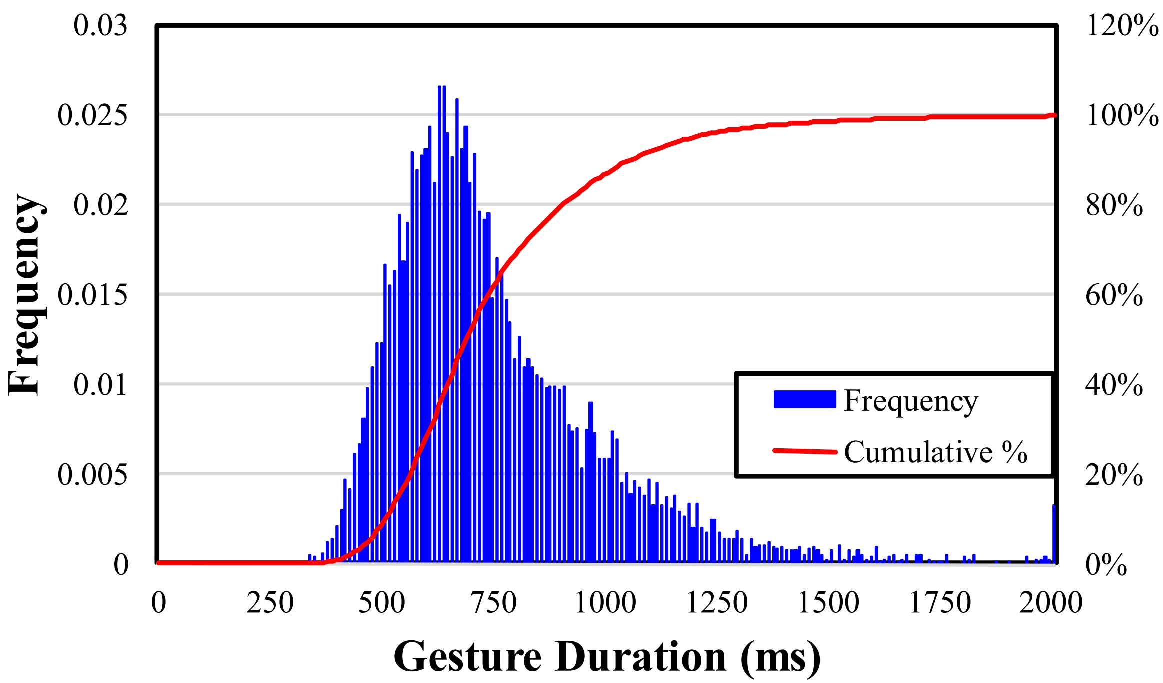


Android and Sensors

- Sensor sampling is non-deterministic
  - "It's ready when it's ready" attitude
- Sample rate fluctuates depending on a number of factors
- Gestures also last varying amounts of time
- Different sensors poll at different rates
- Most machine-learning algorithms expect data vectors of a set size

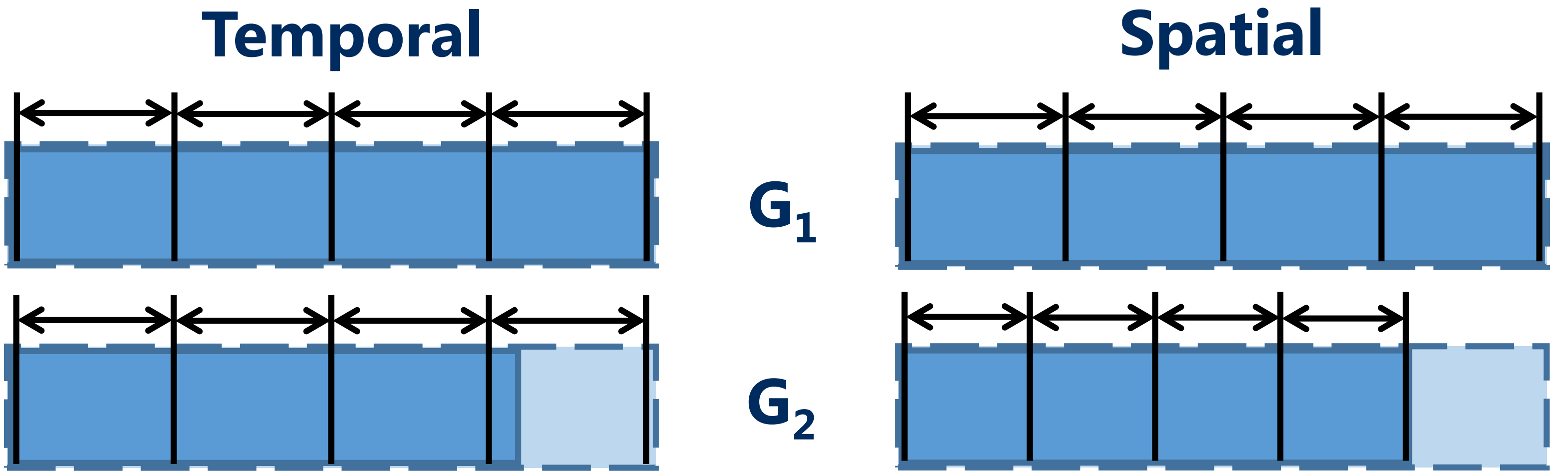
Standardizing Samples

- Gestures varied between 0.4 and 1.4 seconds
- Recorded anywhere between 24 and 162 samples per gesture
  - Also differs depending on sensor



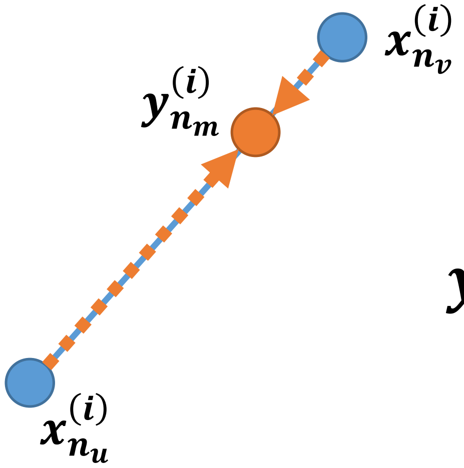
Standardizing Data Size

- Two ways to standardize the data
- "Temporal" Standardization
  - Set gesture time, equidistant sample points
- "Spatial" Standardization
  - Allow unique time per gesture, equal number of samples for each



Interpolating Data

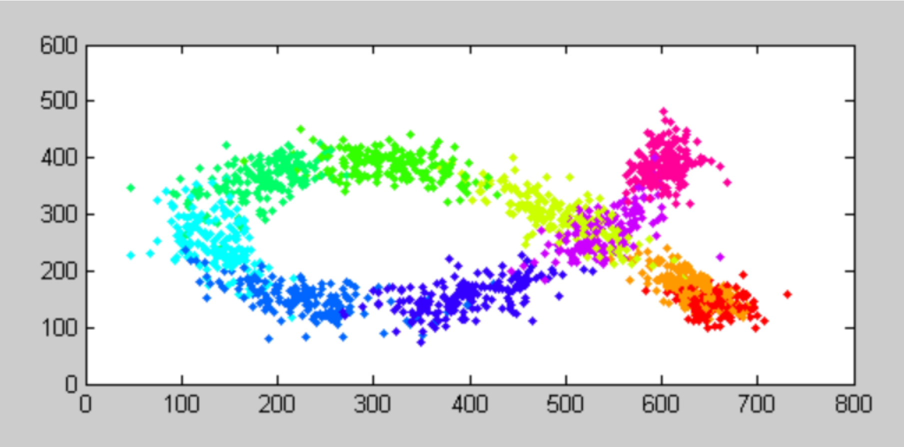
- Discrete sample points do not always occur where needed (temporally) for standardization
- Perform linear interpolation to estimate the sample data at the required points



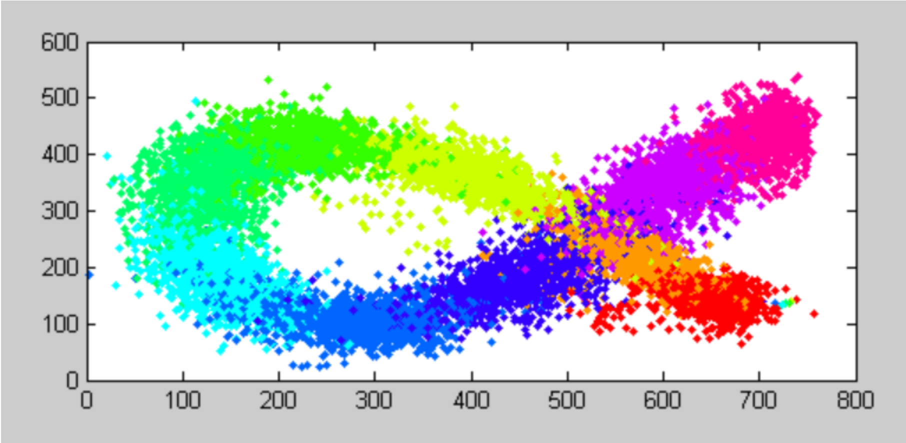
$$y_{n_m}^{(i)} = \frac{t_{x,n_v}^{(i)} - t_{y,n_m}^{(i)}}{t_{x,n_v}^{(i)} - t_{x,n_u}^{(i)}} x_{n_u}^{(i)} + \frac{t_{y,n_m}^{(i)} - t_{x,n_u}^{(i)}}{t_{x,n_v}^{(i)} - t_{x,n_u}^{(i)}} x_{n_v}^{(i)}$$

Normalizing Sensor Data

- Raw sensor values vary in magnitude
- Can artificially weight specific sensor values
- Must "normalize" all data to similar ranges
  - Naïve Normalization
  - Z-Score Normalization
- Examine impact of these, as well as without

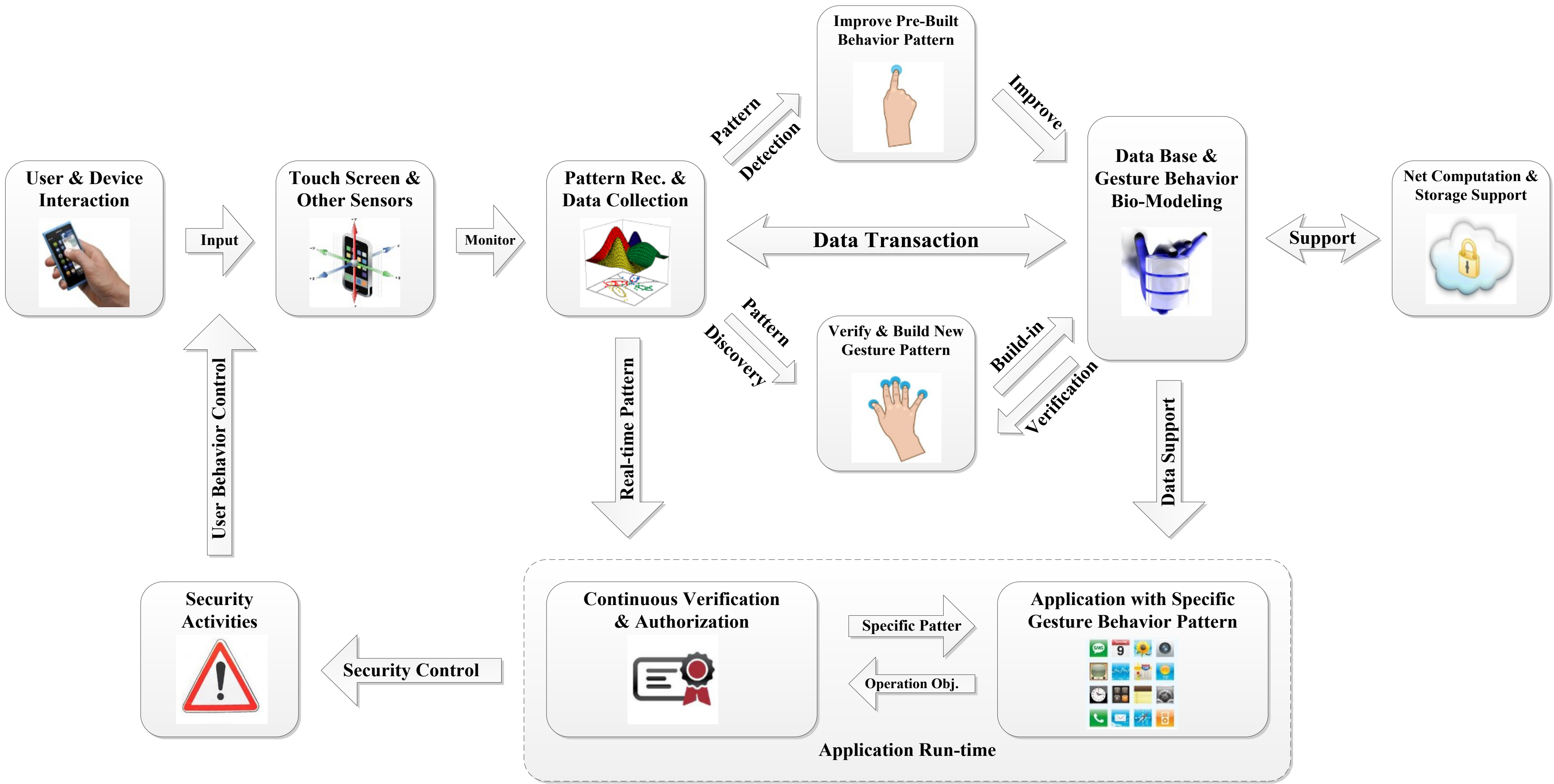


User 1



User 2

SloMo Functionality

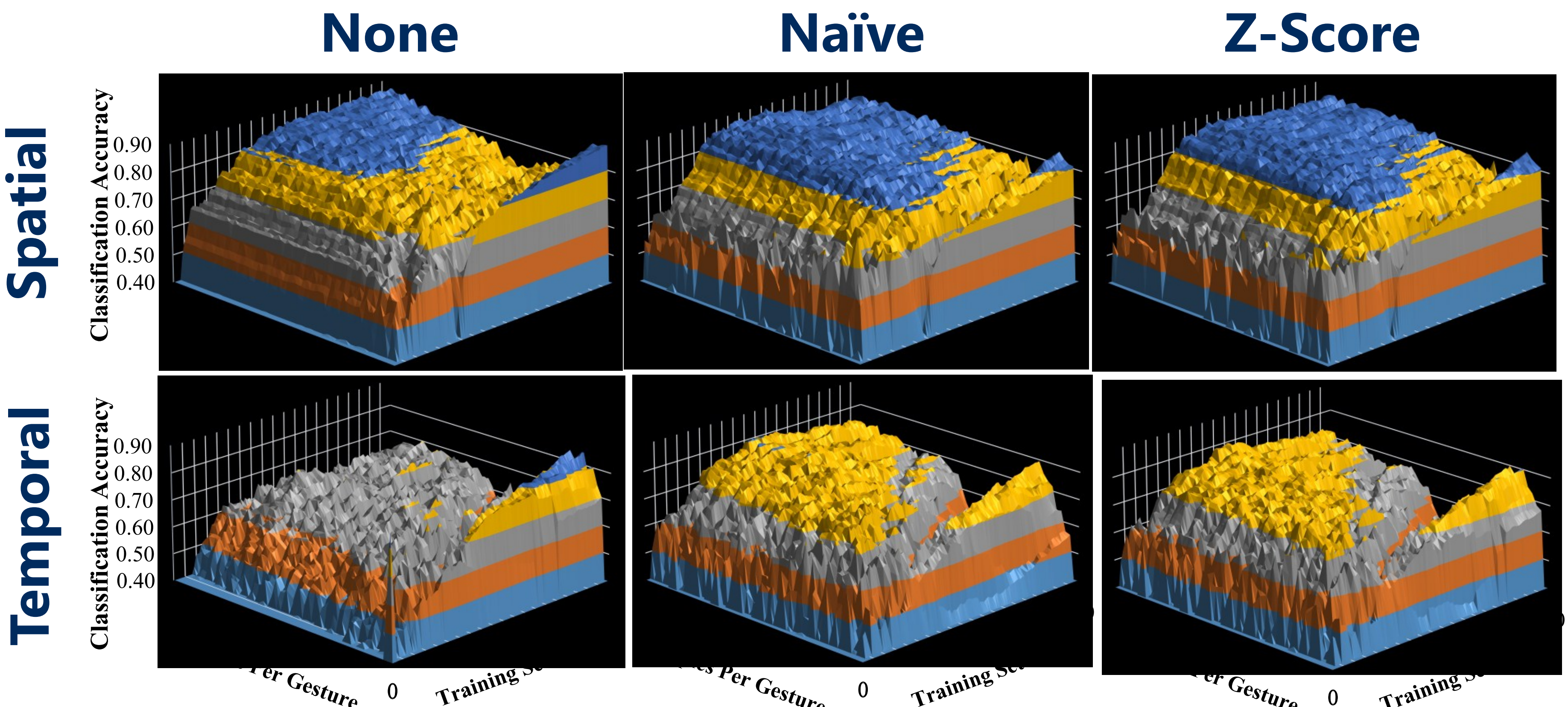


Types of Classification

- One Versus Many (OVM)
  - Identifying a single user out of a group of known users
  - Imagine an iPad which could determine which family member was using it at any given time
- One Versus All (OVA)
  - Identifying whether or not a user is the owner of the device
  - No a priori sample sets for other users
  - Imagine a smartphone that could be used by you but no one else

OVM

- Have sample data from all possible users
- Generate a Gaussian model for each user



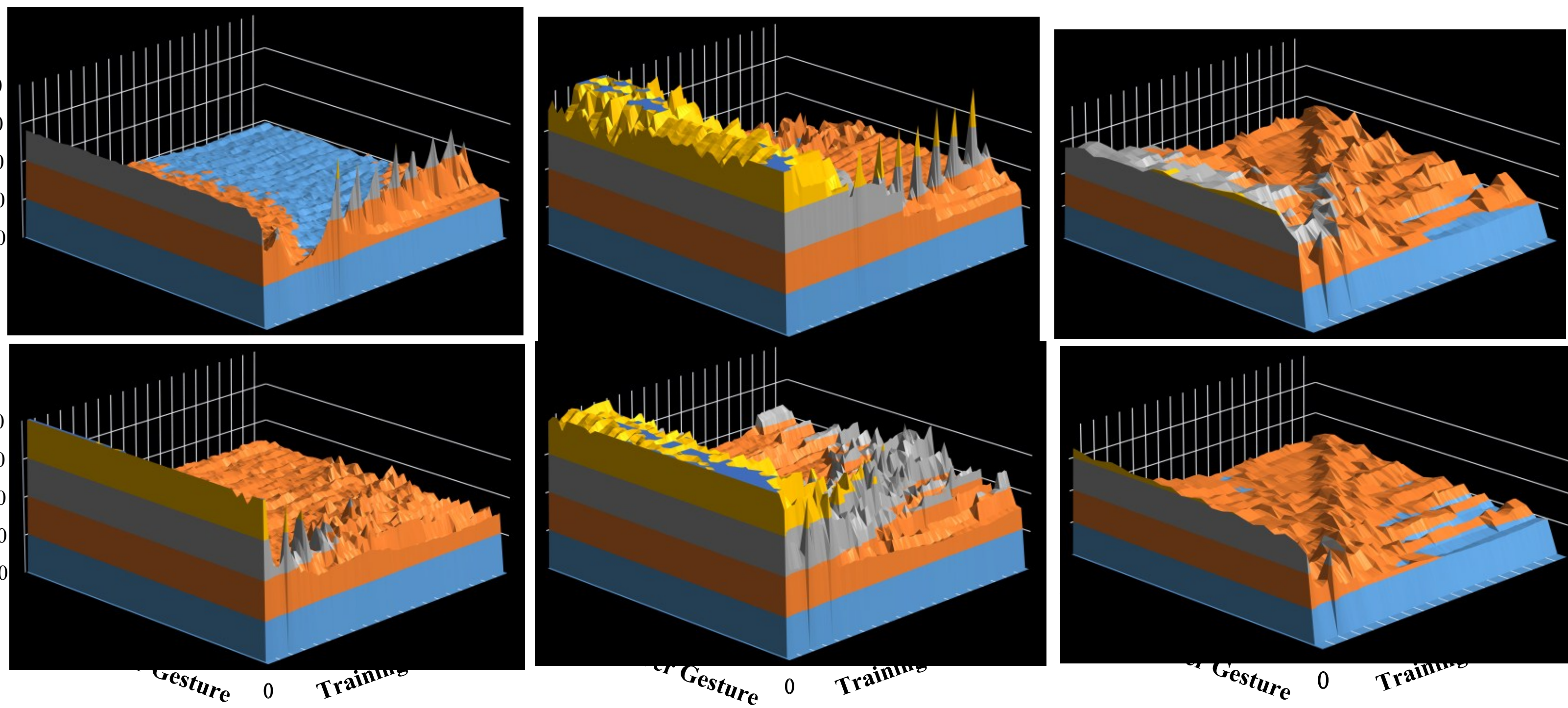
OVA

- Only sample data from a single user
- Use a threshold for Gaussian classifier

None | Naïve | Z-Score

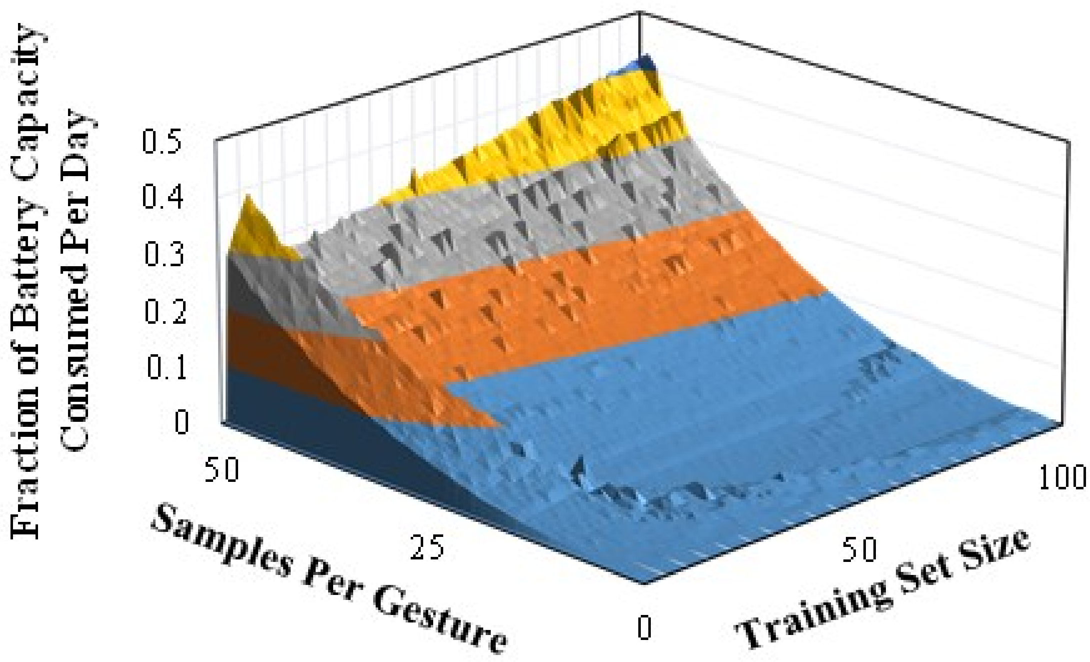
Spatial

Temporal



Takeaways

- Temporal standardization
- No more than 20 training samples required
- Max accuracy achieved with low sample rate



Conclusion

- Shows different classification methods have different data processing requirements
- Indicates ethological information that is shared between all users
- Demonstrates that low sample rate and training set size can yield high accuracy