

Active Authentication on-the-Go

Mobile Gait Biometrics for DARPA Active Authentication Phase II

Yu Zhong, Yunbin Deng, Geoffrey Meltzner, and Greg Pierre-Louis
BAE Systems, Advanced Information Technology
Burlington, MA USA

{yu.zhong,yunbin.deng,geoffrey.meltzner,gregory.pierrelouis}@baesystems.com

October 30, 2014

This research was developed with funding from the Defense Advanced Research Projects Agency (DARPA).



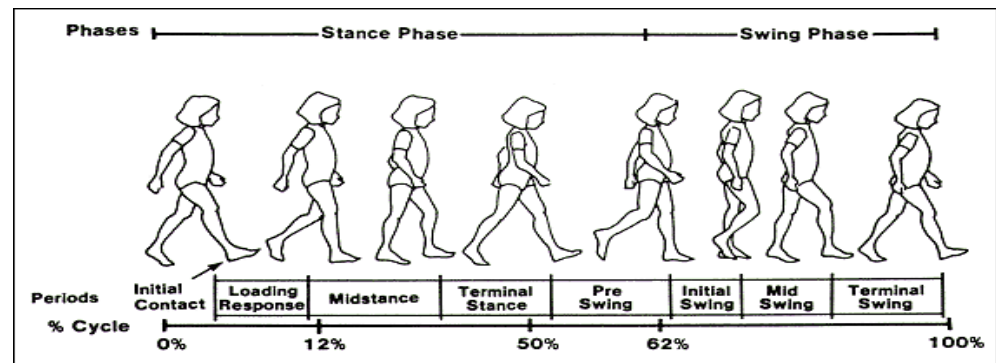
The views, opinions, and/or findings contained in this article/presentation are those of the author/presenter and should not be interpreted as representing the official views or policies, either expressed or implied, of the Department of Defense or the U.S. Government."

Outline

- Background
- Gait Dynamics Images
- i-Vector Authentication
- Data Collection
- Future Steps

Background

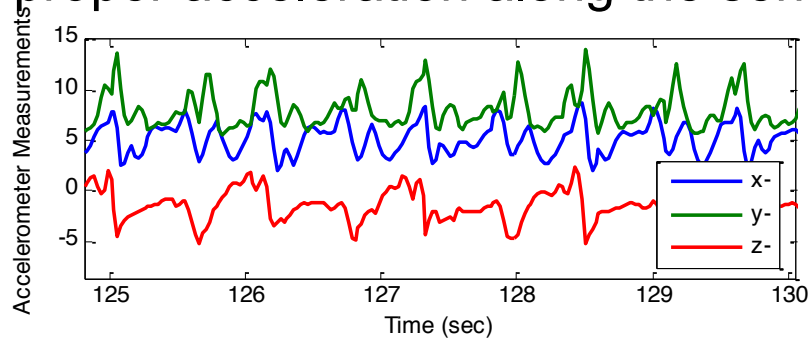
- Increasing demand for truly secure authentication solutions based on user identity.
- Ubiquitous mobile devices embedded with sensors constantly collect data about users and surroundings.
- DARPA's Active Authentication Phase II
 - Explore new pilot biometric modalities that can work in a mobile environment
 - We investigate the use of accelerometers & gyroscopes for gait biometrics
 - Gait is unique due to an individual's specific neuromuscular and musculoskeletal system
 - Potential high accuracy
 - Non-intrusive



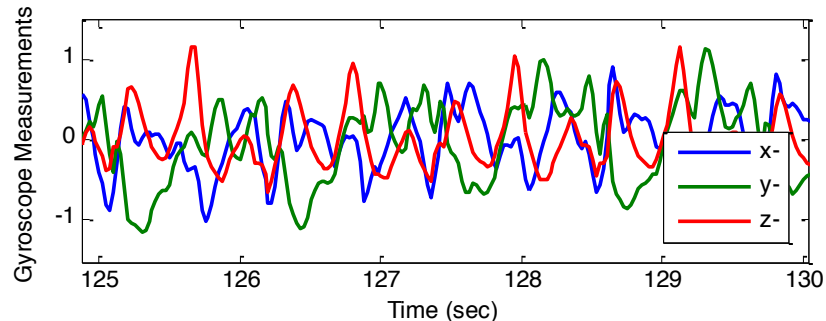
From <http://www.clinicalgaitanalysis.com/history/modern.html>

Accelerometers and Gyroscopes for Gait Biometrics

- An accelerometer measures proper acceleration along the sensor axis.



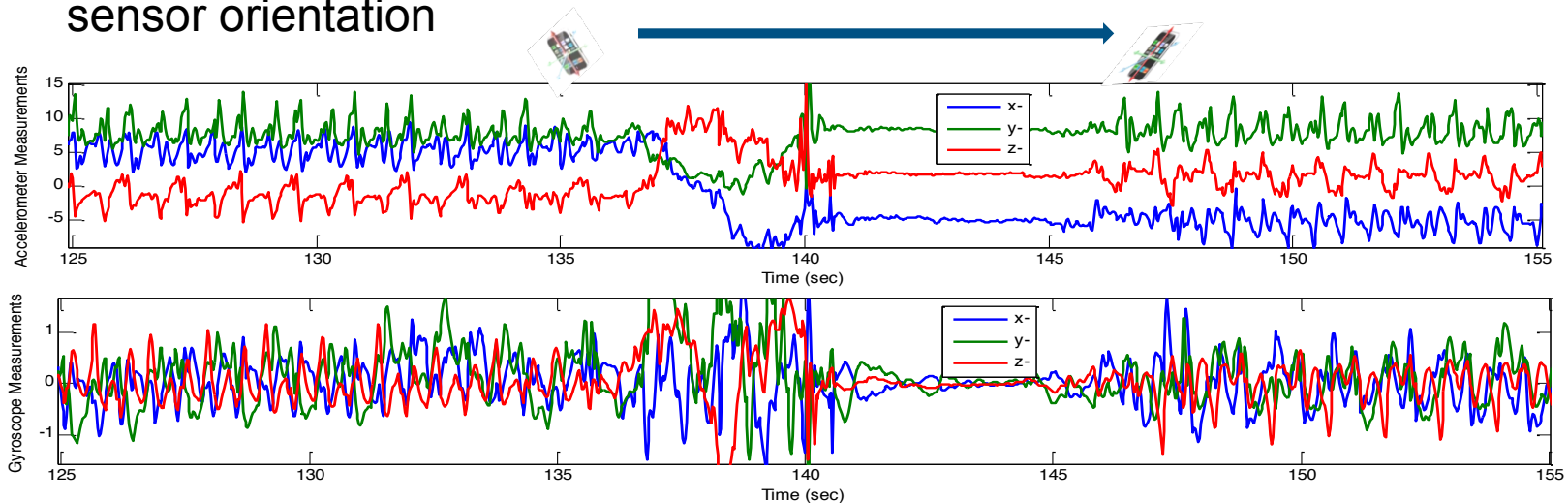
- A rate gyroscope measures the rate of rotation along the sensor axis.



- They combined to provide full 6-dof motion measurements.
- Accelerometers and gyroscopes embedded in mobile devices capture rich body motion cues for gait characterization.
- Promising gait ID results using accelerometers have been published.

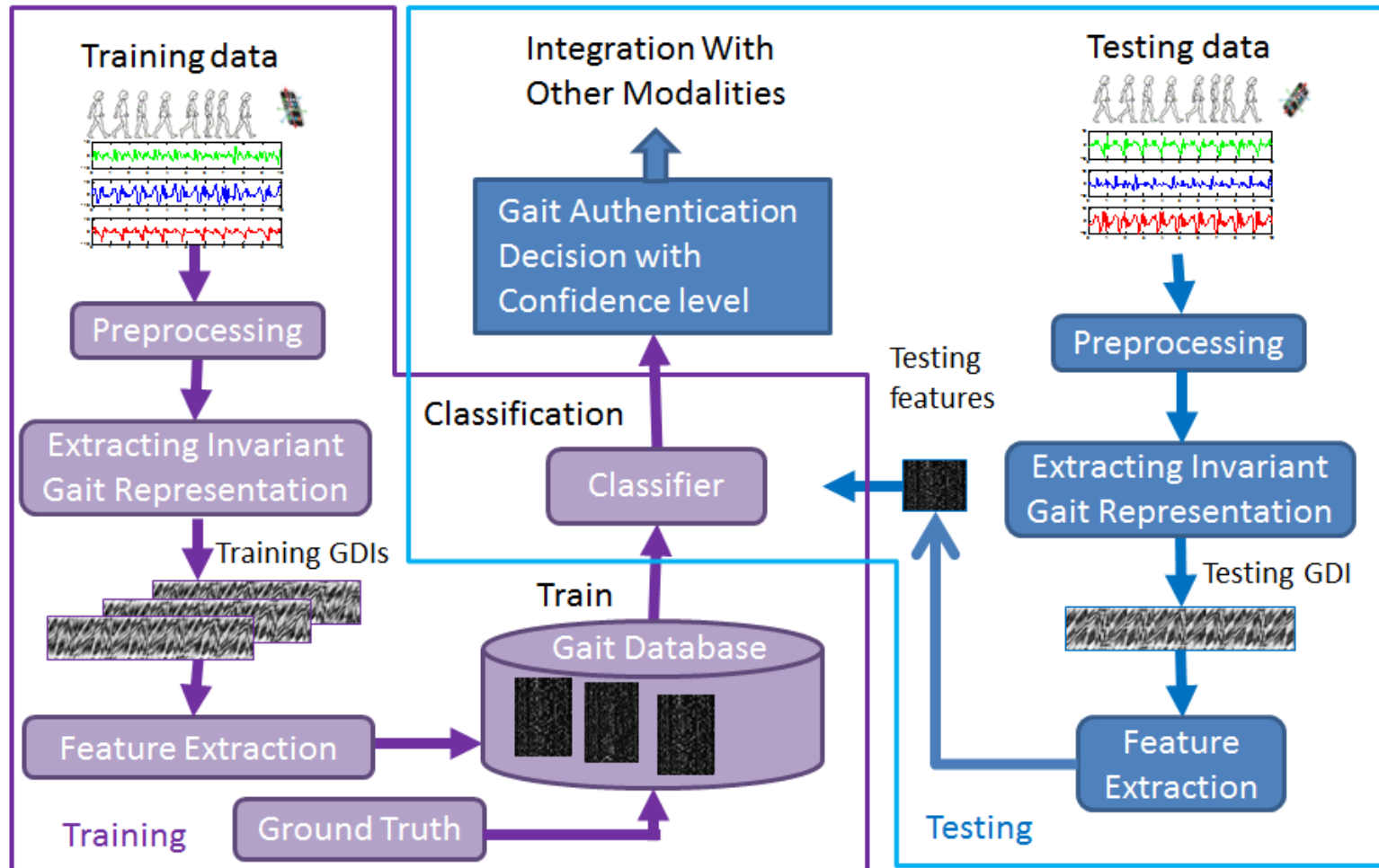
Gait Analysis Faces Significant Challenges in Real Applications

- Data measurements depend on where and how the device is placed
 - Locomotion signatures are different for various body parts
 - Even for the same location at a specific body part, captured data change with sensor orientation



- Existing studies assumed controlled experimental settings
- Further complication with varying walking pace
- Physical load, footwear, floor condition, and emotional state may each influence how one walks

Active Authentication On-the-go Overview



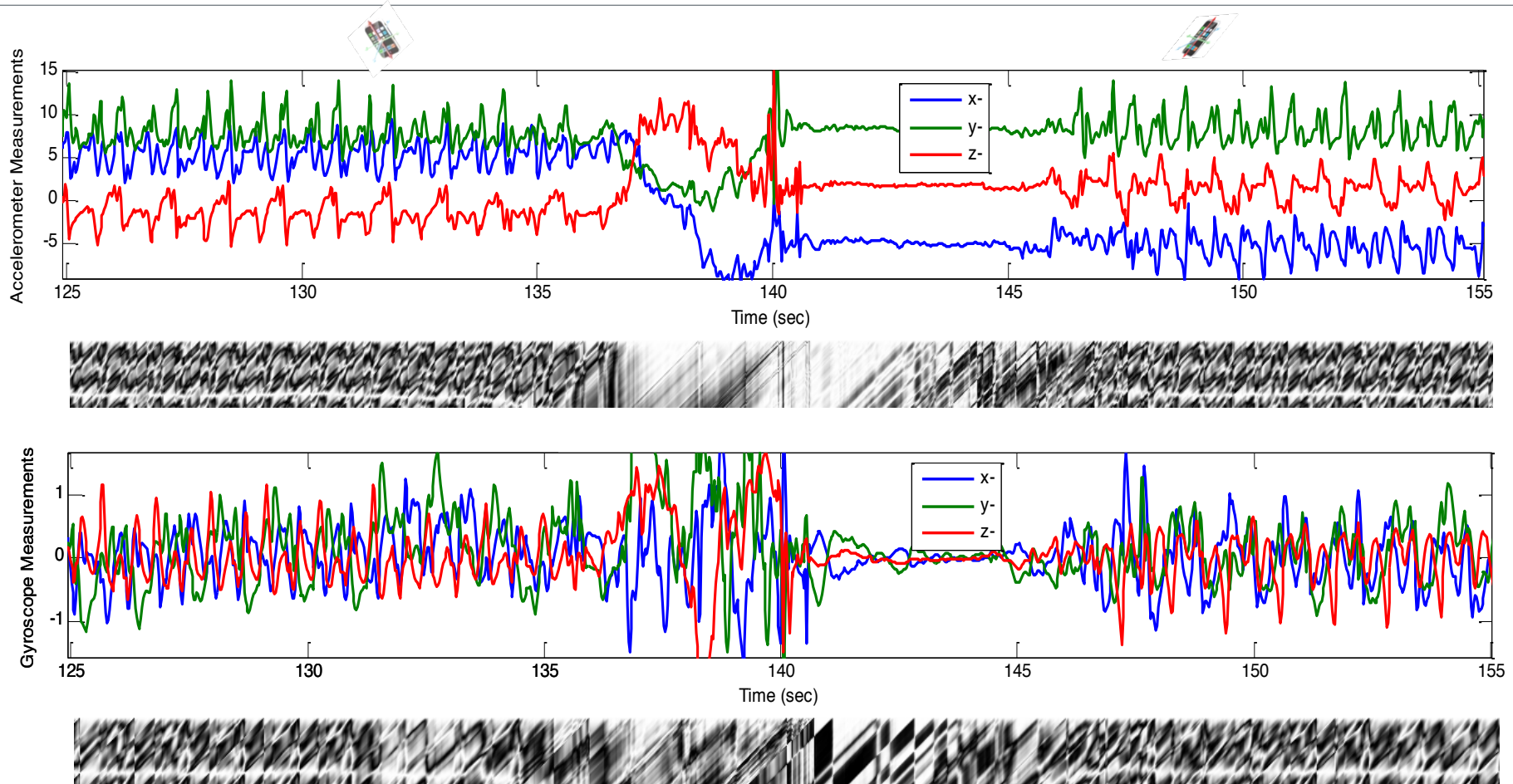
Outline

- Background
- Gait Dynamics Images

Gait Dynamics Images

- Compute innovative Gait Dynamics Image (GDI) representations from raw inertial data
 - Invariant to sensor orientation changes
 - Highly discriminative
 - Allows for dynamic gait cycle estimations to compensate for pace variation
 - Applicable to both accelerometer data and gyroscope data
 - Invariant to symmetry transforms in the raw 3D data
 - Invariant to concatenations of rotation and symmetry transforms
 - laterally symmetric human anatomy typically creates symmetric locomotion for the left and right sides of the body
 - Enables GDIs from a phone placed in one pocket to be matched with GDIs from phones in the opposite side pocket, thus further ease the sensor placement constraint

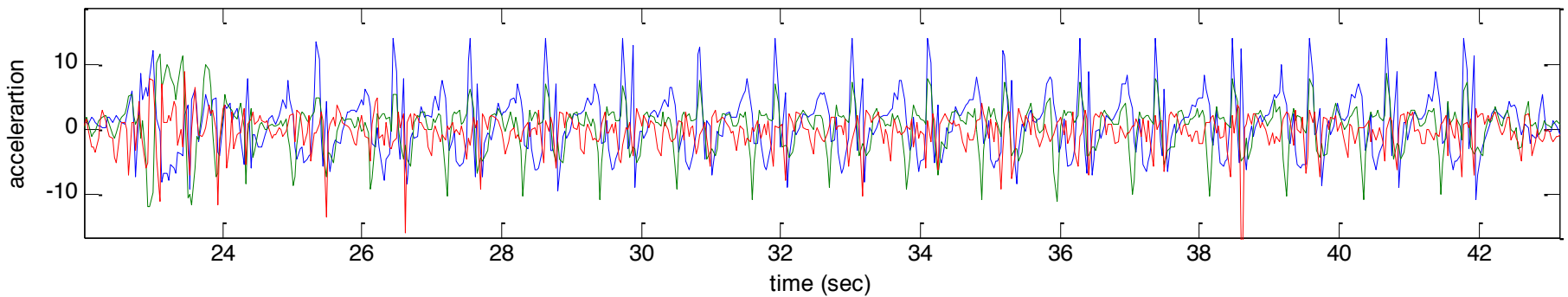
GDI's Are Sensor Orientation Invariant



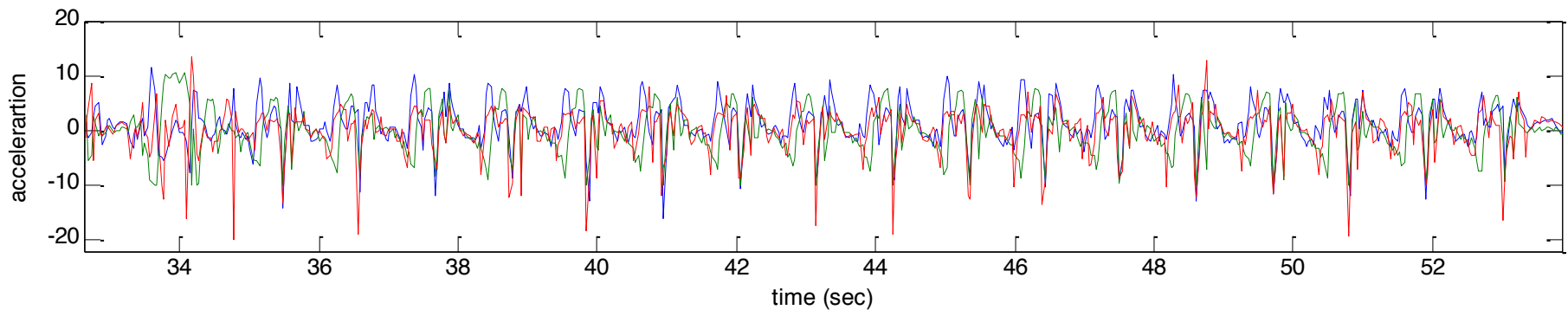
As sensor orientation changes, the raw data become drastically different while their GDIs remain consistent due to their invariance in sensor orientation

Inertial sensors capture different locomotion depending on placement

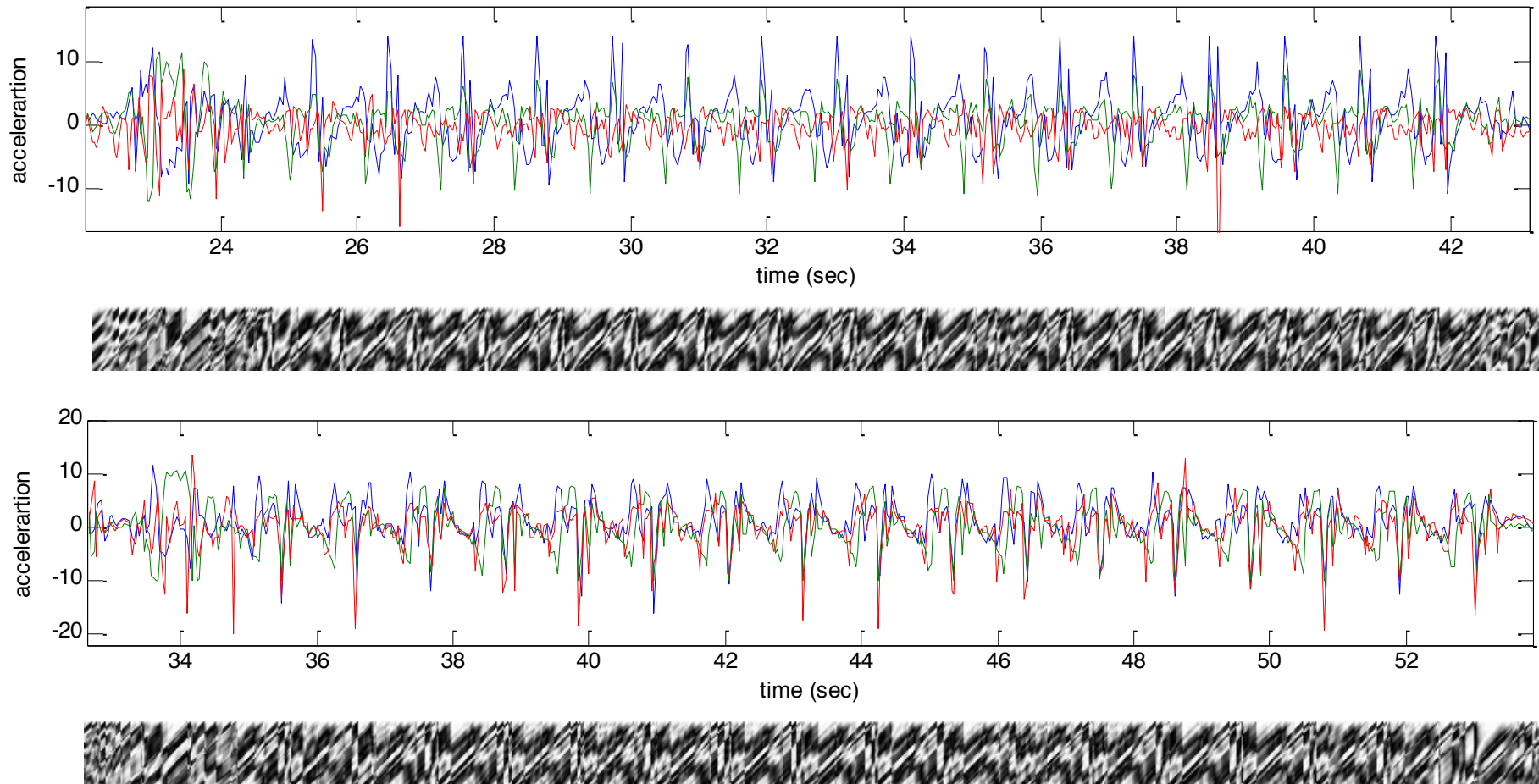
Phone in front right pocket



Phone in front left pocket



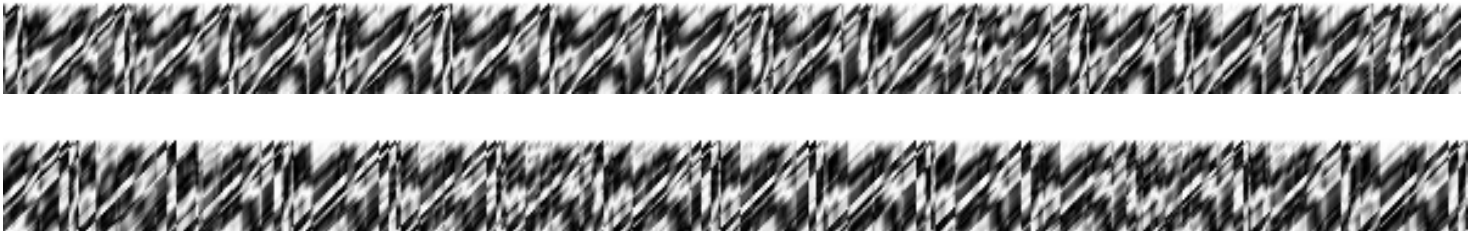
GDIs Are Invariant to Symmetry Transforms to data



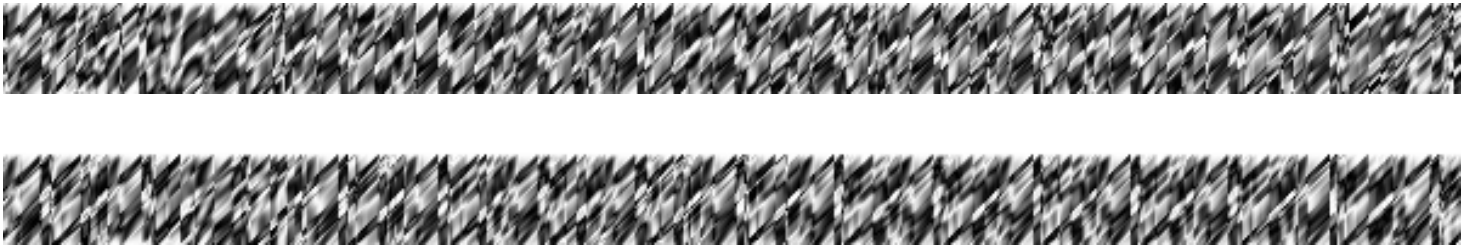
Consistent GDIs for phones placed in the pockets from opposite sides

Example GDIs from Phones in Pockets from Opposite Sides

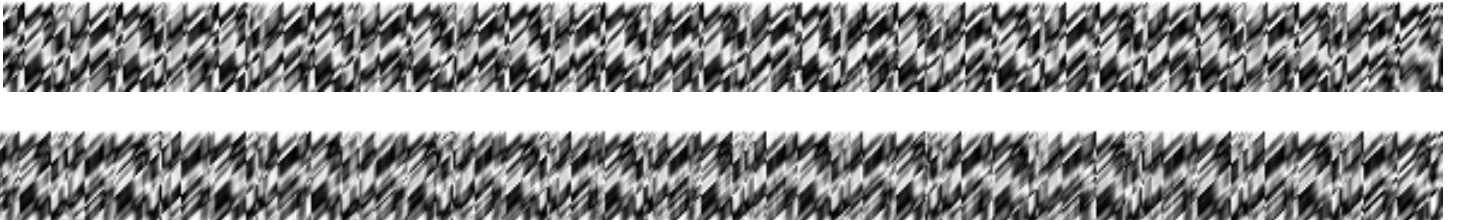
Subject 1



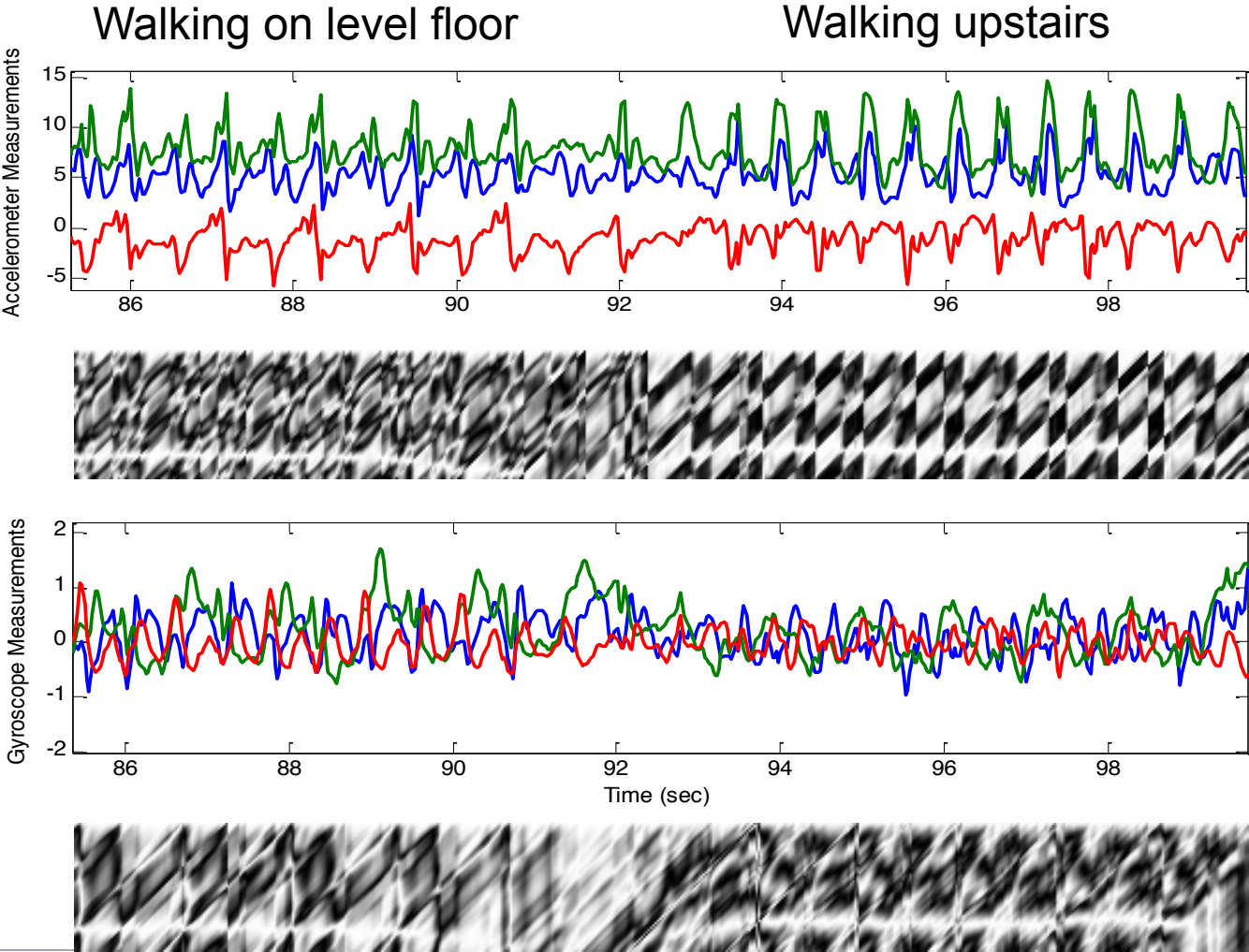
Subject 2



Subject 3

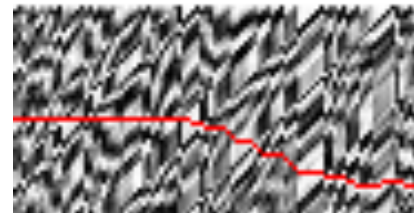
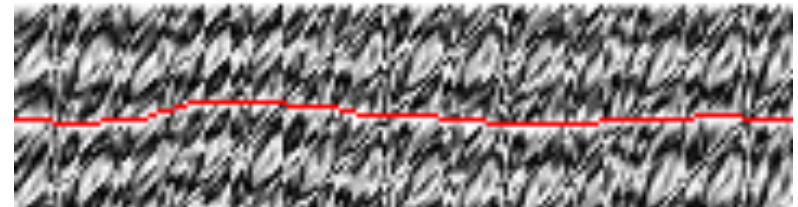
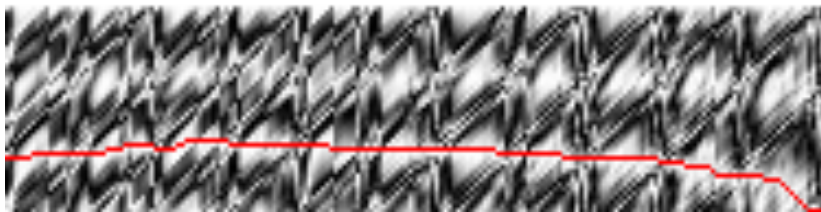


GDIs Capture Activity Patterns



Gait Cycle Estimation Using GDIs

- Dynamically estimate gait cycles to compensate for varying pace for realistic gait biometrics



Outline

- Background
- Gait Dynamics Images
- **i-Vector Authentication**

I-Vector Model on GDIs for Gait Authentication

i-vector Extraction Procedures

- Universal Background Model
- Super-Vector Extraction
- Factor Analysis

Key Advantages

- Single vector representation of Gait sequence
- Facilitate factor analysis and discriminative analysis

Experimental Validation

- Accelerometer
- Gyroscope
- Sensor fusion

I-Vector Extraction, Step 1: GDIs to super-vector

Universal Background Model (UBM):

- Pool GDIs from all subjects and build a global Gaussian mixture model (GMM) on training data.
- Start with diagonal-covariance GMM
- Train full-covariance GMM: Ω with C mixture

Super-Vector

- Given input feature vectors (GDIs) of L frames $\{y_1, y_2, \dots, y_L\}$, dimension F
- Compute posterior probability of each Gaussian component
- Collect Baum-Welch statistics

$$\tilde{F}_c = \sum_{t=1}^L P(c|y_t, \Omega)(y_t - m_c)$$

$$N_c = \sum_{t=1}^L P(c|y_t, \Omega)$$

- Supervector is obtained by concatenating all Baum-Welch statistics to form a single vector of fixed dimension $C \cdot F$ for a gait sequence of arbitrary length L

I-Vector Extraction, Step 2: super-vector to i-Vector

Total Variability Space: A simple model for all possible variability in gait (such as sensor location, walking style, clothing and foot wear)

$M = m + Tw$ (where M is supervector, m is subject independent, T is a rectangular matrix of low rank, and w is the identity vector, or i-vector)

Train i-Vector Extractor: i.e., Learn the total variability matrix T and residue variability covariance matrix Σ using EM algorithm.

Extract i-Vectors:

$$w = (I + T^t \Sigma^{-1} N(u) T)^{-1} . T^t \Sigma^{-1} \tilde{F}(u)$$

where $N(u)$ is diagonal matrix whose diagonal blocks are $Nc \cdot I$.

Cosine Distance Scoring:

$$\text{score}(w_{\text{target}}, w_{\text{test}}) = \frac{\langle w_{\text{target}}, w_{\text{test}} \rangle}{\|w_{\text{target}}\| \|w_{\text{test}}\|} \begin{matrix} \geq \\ \leq \end{matrix} \theta$$

Experiments on Osaka Gait Dataset

Osaka-ISIR Gait Database, Inertial Sensor Dataset

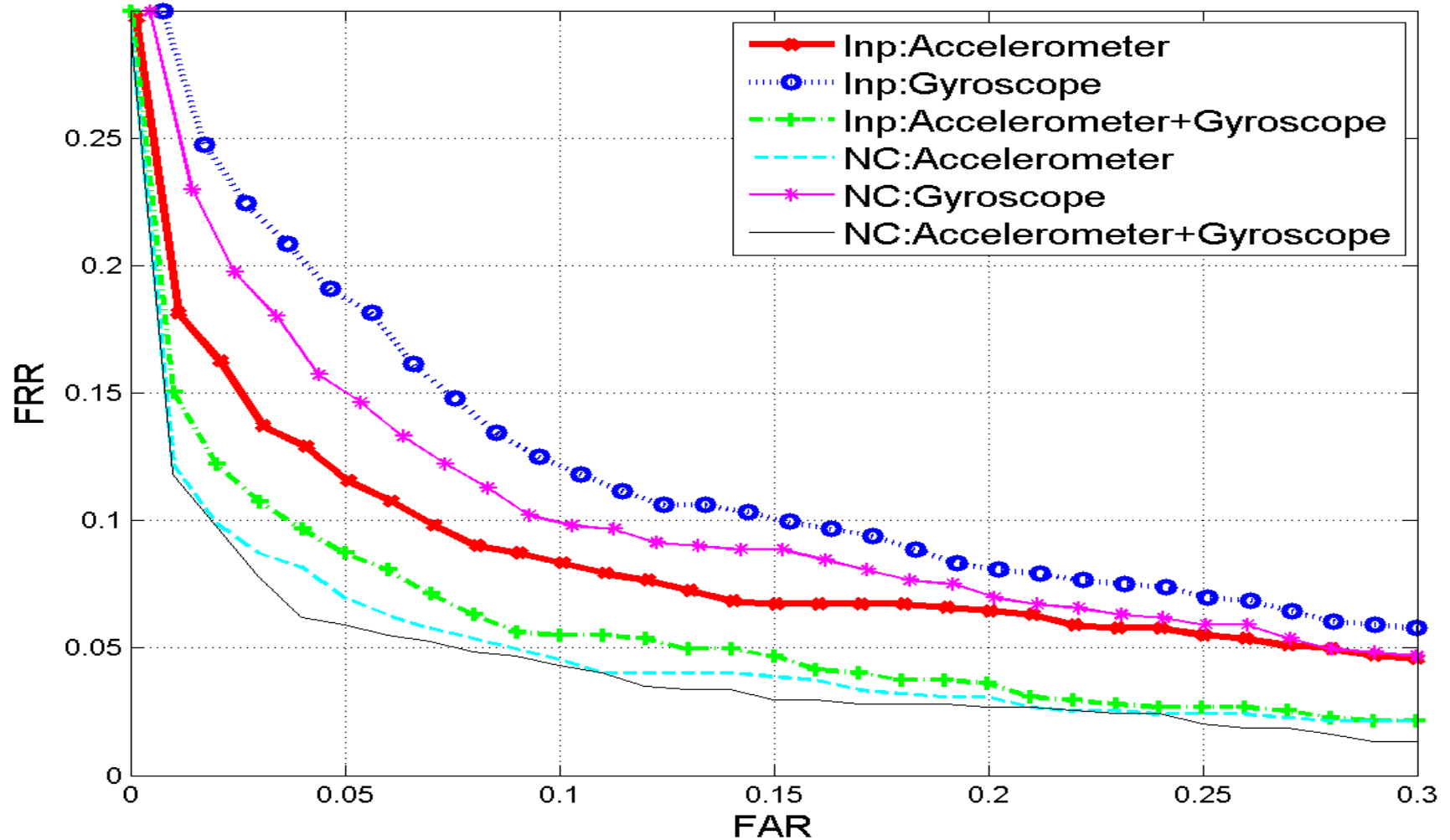
- Largest public available data contains 744 subjects.
- Each subject has one training and one test token
- Contain both Accelerometer and Gyroscope sensory data
- Controlled sensor placement

i-Vector Extraction

- GDIs from training set were used to build global GMM with 800 mixtures
- i-vectors of 60 dimension were extracted for training and testing data
- Conducted a total number of $744 \times 744 = 553,536$ authentication tests
- Experiments on Accelerometer only, Gyroscope only, and Score fusion

Gait Biometrics Performance on Osaka-ISIR Dataset

GDI+iVector Gait Authentication Performance



GDI+i-vectors Outperforms Published Results

Method	Accuracy (EER %)		
	Accelerometer	Gyroscope	Fused
Gafurove et al. [2]	15.8 [4]	NA	NA
Derawi et al. [1]	14.3 [4]	NA	NA
Liu et al. [3]	14.3 [4]	NA	NA
Ngo et al. [4]	13.5 [4]	20.2 [4]	NA
Inner Product GDI + i-vector	8.9	11.3	7.1
Cosine Similarity GDI + i-vector	6.8	10.9	5.6

1. M.O. Derawi, P.Bours, and K.Holien. Improved cycle detection for accelerometer based gait authentication. IEEE 6th Int'l Conf. *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP)*, 2010.
2. D. Gafurov, E. Snekenes, P. Bours, Improved gait recognition performance using cycle matching, IEEE 24th Int'l Conf. Advanced Information Networking and Applications Workshops (WAINA), 2010.
3. R. Liu, J. Zhou, and X. Hou, A wearable acceleration sensor system for gait recognition, *2nd IEEE Conf. Industrial Electronics and Applications*, 2007.
4. T.T. Ngo, Y. Makihara, H. Nagahara, Y. Mukaigawa, and Y. Yagi, The Largest Inertial Sensor-based Gait Database and Performance Evaluation of Gait Recognition, *Pattern Recognition*, 47(1), 2014.

Outline

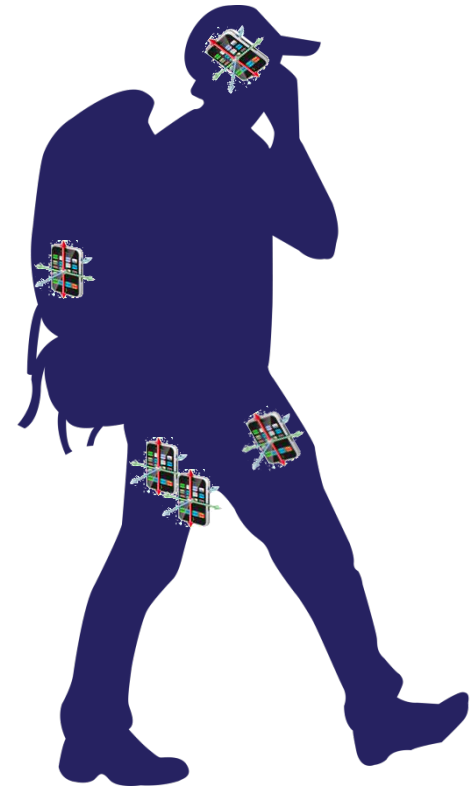
- Background
- Gait Dynamics Images
- i-Vector Authentication
- **Data Collection**

Data Collection Effort

- Goal: Collect gait related data from sensors on board mobile phones to support development, testing, and characterization of gait based authentication algorithms.
- I-vector approach needs training data from several subjects to create Universal Background Model
- Need to characterize and mitigate the effects of training and testing condition mismatch, e.g...
 - Models trained with phone in pocket but phone is carried in backpack during use.
 - Models trained using normal walking pace, but tested on faster/slower pace

Data Collection Effort - Protocol

- We are in the process of collecting data from a total of 100 subjects
 - Collected from 81 so far
- Each subject outfitted with 6 Nexus 5 phones:
 - 2 in front pants pockets (L/R), 2 in rear pants pockets (L/R), 1 in backpack, and 1 in hand
 - Phones collect 3-axis accelerometer and gyroscope signals
 - Signals sampled at 100 Hz.
- Subjects instructed to walk in a loop x 4
 - Includes walking on flat surface as well as ascending and descending stair cases
 - Includes changes in walking speed
 - 17" laptop added to backpack for 4th loop



Data Collection Effort – Current Authentication Status

- Based on 16 subjects

Phone	# of Tests	GDI+ i-vector EER (%)	GDI+ i-vector + LDA EER (%)
front_left	8,416	2.47	1.71
front_right	7,904	4.25	2.83
back_left	7,050	4.89	3.19
back_right	6,975	4.09	2.80
backpack	7,344	5.66	3.05
hand	4,592	8.36	6.97
Average	7,047	4.95	3.43

Outline

- Background
- Gait Dynamics Images
- i-Vector Authentication
- Data Collection
- **Future Steps**

Future Steps

- Complete data collection effort
- Continuing algorithm improvements
 - Model of gait sequence with gait cycle detection
 - Different distance measure for GDIs and i-vectors
- Implementation and integration of i-vector classifier into real time Android App
- Performance analysis on collected data

Thank you

