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On The Instability of Sensor Orientation in Gait Verification on Mobile Phone

Thang Hoang[†], Deokjai Choi[†], Thuc Nguyen[‡]

[†] Faculty of Information Technology, Saigon Technology University, Vietnam
thang.hoangminh@stu.edu.vn
[†] Dept. of Electronics & Computer Engineering, Chonnam National University, South Korea
dchoi@jnu.ac.kr
[‡] Faculty of Information Technology, Ho Chi Minh University of Science VNU-HCMC, Vietnam
ndthuc@fit.hcmus.edu.vn

Outline

- ❖ Introduction
- ❖ Motivation & Contributions
- ❖ Proposed Methods
  - Solution for The Instability of Sensor Orientation
  - Machine-Learning Based Gait Verification Model
- ❖ Experiments
- ❖ Conclusion

Introduction

- The number of mobile subscriptions is forecasted to reach 9.3 billion by 2019, 5.6 billion of which will be for smart phones.
- Personal data have being accumulated more and more in the mobile phone.

  → ***Sensitive data inside are becoming more vulnerable to be illegally exploited!***.

- **Well-known authentication methods**
  - Secret key (PIN, passwords, visual patterns)
  - Philological biometrics (face, fingerprint)

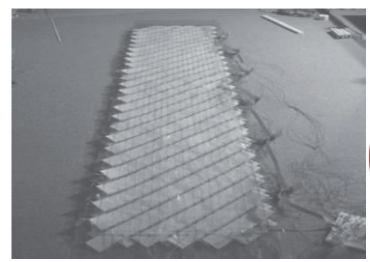
  Limitations

  - Password management (remembrance, storage)
  - Imitation of biometric samples
  - Obtrusive in frequent use

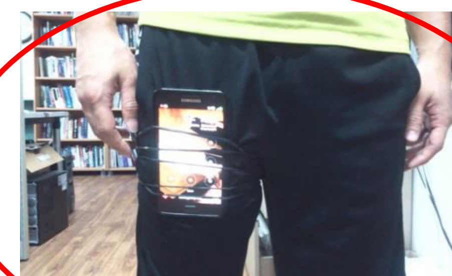
Motivation

- Gait has been introduced as an effective behavioral biometrics which is ***difficult to be counterfeited.***
- Typical gait-based authentication techniques

1. Machine Vision Based



2. Floor Sensor Based



3. Wearable Sensor Based

- Several wearable sensor based gait authentication schemes have been proposed since 2005 [1].
  - **Sensors used:** 2D/3D accelerometer, gyroscope sensor, orientation sensor

Potential drawbacks!!

- Ideal acquisition environment (e.g., sensor is always fixed)
- High error rates (~ 10 – 20%)

Contributions

1. Overcome the instability of sensor orientation during data acquisition
   - *The device can be put freely in the pocket → more practical*
2. Propose a novel Machine Learning-based gait recognition scheme for verification/ identification
   - *Enhance the accuracy rates*

Limitation

- The major location of the device stills need to be fixed

The Instability of Sensor Orientation

Problem statement

The shape of gait signals acquired by 3D accelerometer depends on the relative orientation between the mobile and its carrier

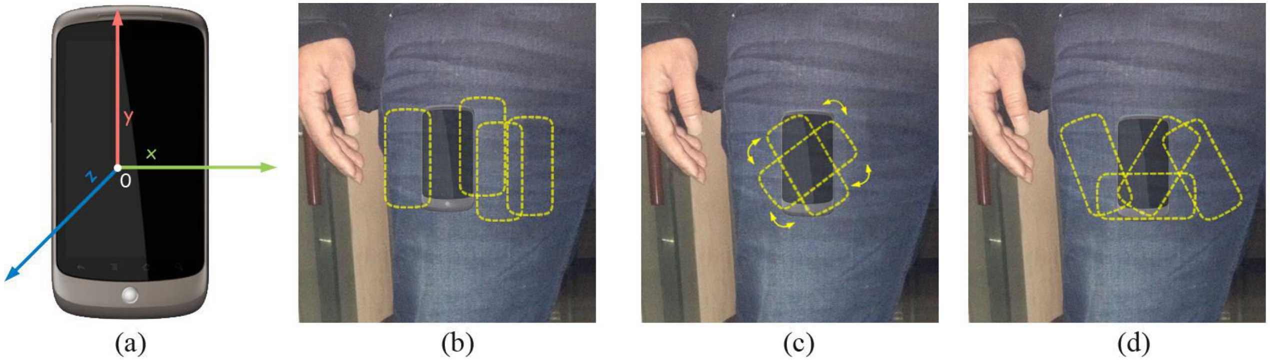


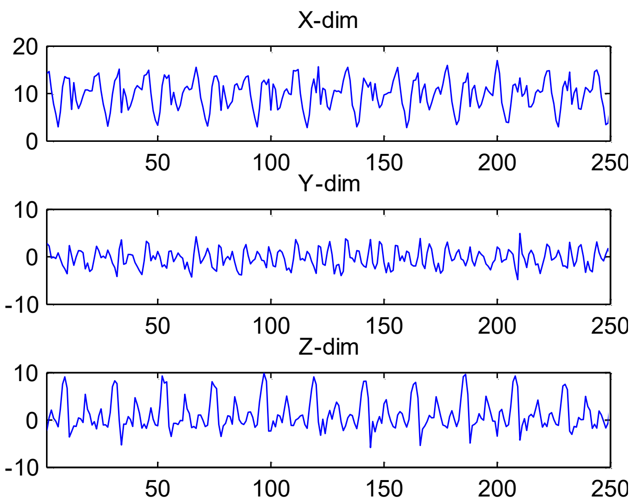
Fig. 1. (a) Mobile coordinate system, (b) minor misplacement, (c) disorientation error and (d) both cases

Sensor disorientation makes the acquired signals in each separate dimension dissimilar.

The Instability of Sensor Orientation

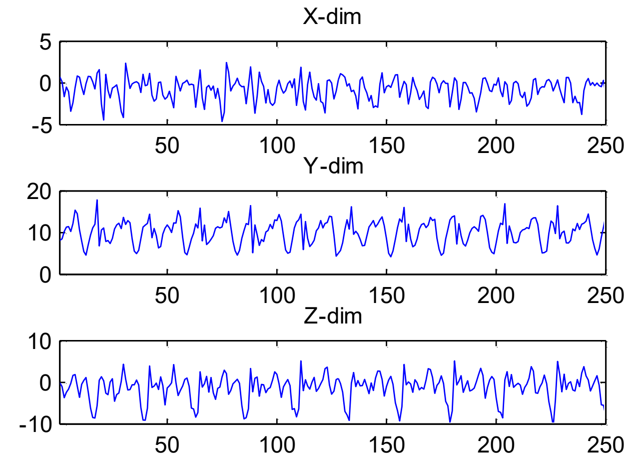
Problem statement

Example:

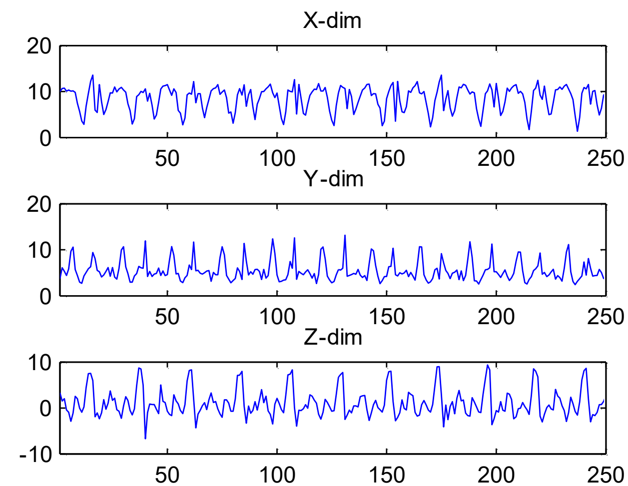


Session 1

Session 2



Session 3



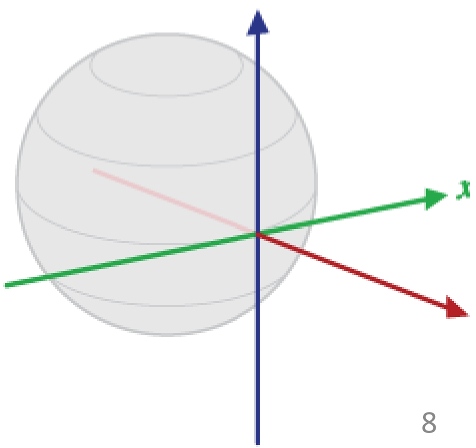
Gait signal of the same subject walking in 3 sessions with different sensor orientation setup.

The Instability of Sensor Orientation

Solution

Representing gait signals from the instable coordinate system (mobile phone) to a stable one

***Earth** is selected to be the fixed coordinate system*



The Instability of Sensor Orientation

Solution

<u>Types of sensor data need to be acquired:</u>

1. Acceleration data (accelerometer)
2. Orientation data (orientation sensor)
3. Gravitational acceleration data (gravity sensor)

$$\mathbf{a} = (a^{(X)}, a^{(Y)}, a^{(Z)})$$
$$\mathbf{g} = (g^{(X)}, g^{(Y)}, g^{(Z)})$$
$$\mathbf{o} = (\alpha, \beta, \gamma)$$

Data collected after a walking session

$$\mathbf{A} = \begin{bmatrix} \mathbf{a}_1 & \dots & \mathbf{a}_i & \dots & \mathbf{a}_n \end{bmatrix}^\top \in \mathbb{R}^{n \times 3}$$

$$\mathbf{G} = \begin{bmatrix} \mathbf{g}_1 & \dots & \mathbf{g}_i & \dots & \mathbf{g}_n \end{bmatrix}^\top \in \mathbb{R}^{n \times 3}$$

$$\mathbf{O} = \begin{bmatrix} \mathbf{o}_1 & \dots & \mathbf{o}_i & \dots & \mathbf{o}_n \end{bmatrix}^\top = \begin{bmatrix} \alpha_1 & \beta_1 & \gamma_1 \\ \vdots & \vdots & \vdots \\ \alpha_i & \beta_i & \gamma_i \\ \vdots & \vdots & \vdots \\ \alpha_n & \beta_n & \gamma_n \end{bmatrix} \in \mathbb{R}^{n \times 3}$$

The Instability of Sensor Orientation

Solution

1. Remove gravitational acceleration components in the gait signals

$$\mathbf{A} \leftarrow \mathbf{A} - \mathbf{G}$$

2. Transform the gravity-free signal to the Earth coordinate system

$$\mathbf{a}_i \leftarrow \mathbf{a}_i \mathbf{R}_i$$

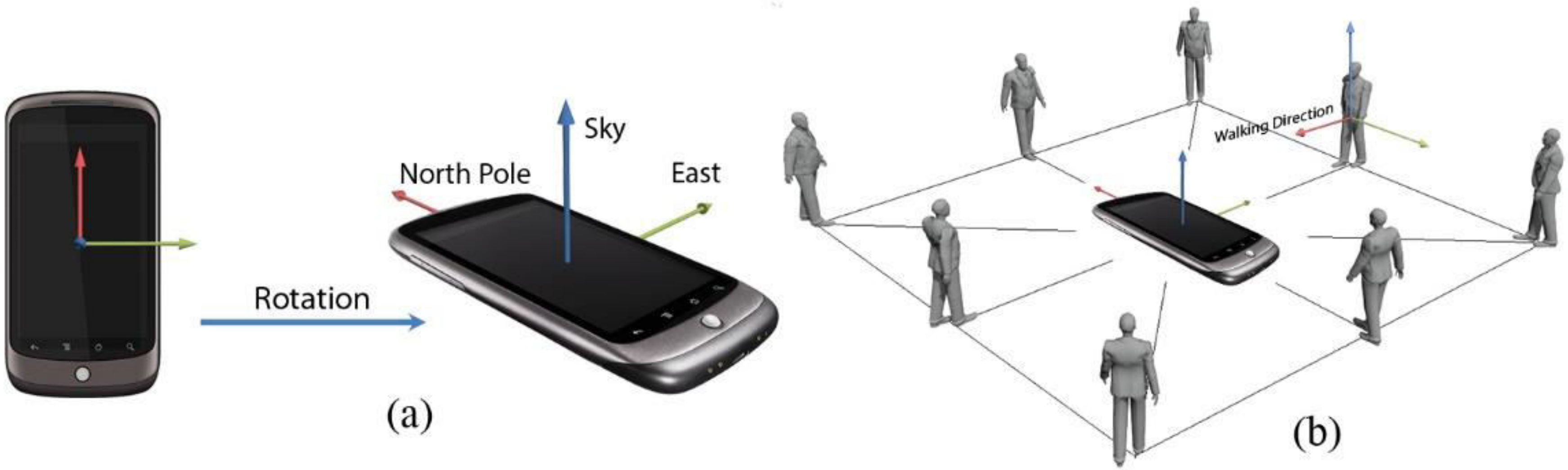
where $\mathbf{R}_i$ *is the rotation matrix calculated from each rotation vector* $\mathbf{o}_i$ *by*

$$\mathbf{R}_i = \begin{bmatrix} \cos\alpha_i \cos\gamma_i - \sin\alpha_i \sin\beta_i \sin\gamma_i & \sin\alpha_i \cos\beta_i & \cos\alpha_i \sin\gamma_i + sin\alpha_i \sin\beta_i \cos\gamma_i \\ -\sin\alpha_i \cos\gamma_i - \cos\alpha_i \sin\beta_i \sin\gamma_i & \cos\gamma_i \cos\beta_i & -\sin\gamma_i \sin\gamma_i + \cos\alpha_i \sin\beta_i \cos\gamma_i \\ -\cos\beta_i \sin\gamma_i & -\sin\beta_i & \cos\beta_i \cos\gamma_i \end{bmatrix}$$

The Instability of Sensor Orientation

Problem

By using the Earth coordinate system, transformed gait signals in the separate X, Y dimensions ($\mathbf{a}^{(X)}, \mathbf{a}^{(Y)}$) are dissimilar as the user can walk in any direction in the horizontal plane



(a) (b)

The Instability of Sensor Orientation

Solution

The combined signal of $X-Y$ $\mathbf{a}^{(XY)}$ is used instead, along with the signal of magnitude dimension $\mathbf{a}^{(M)}$ to re-form the 3D gait signal

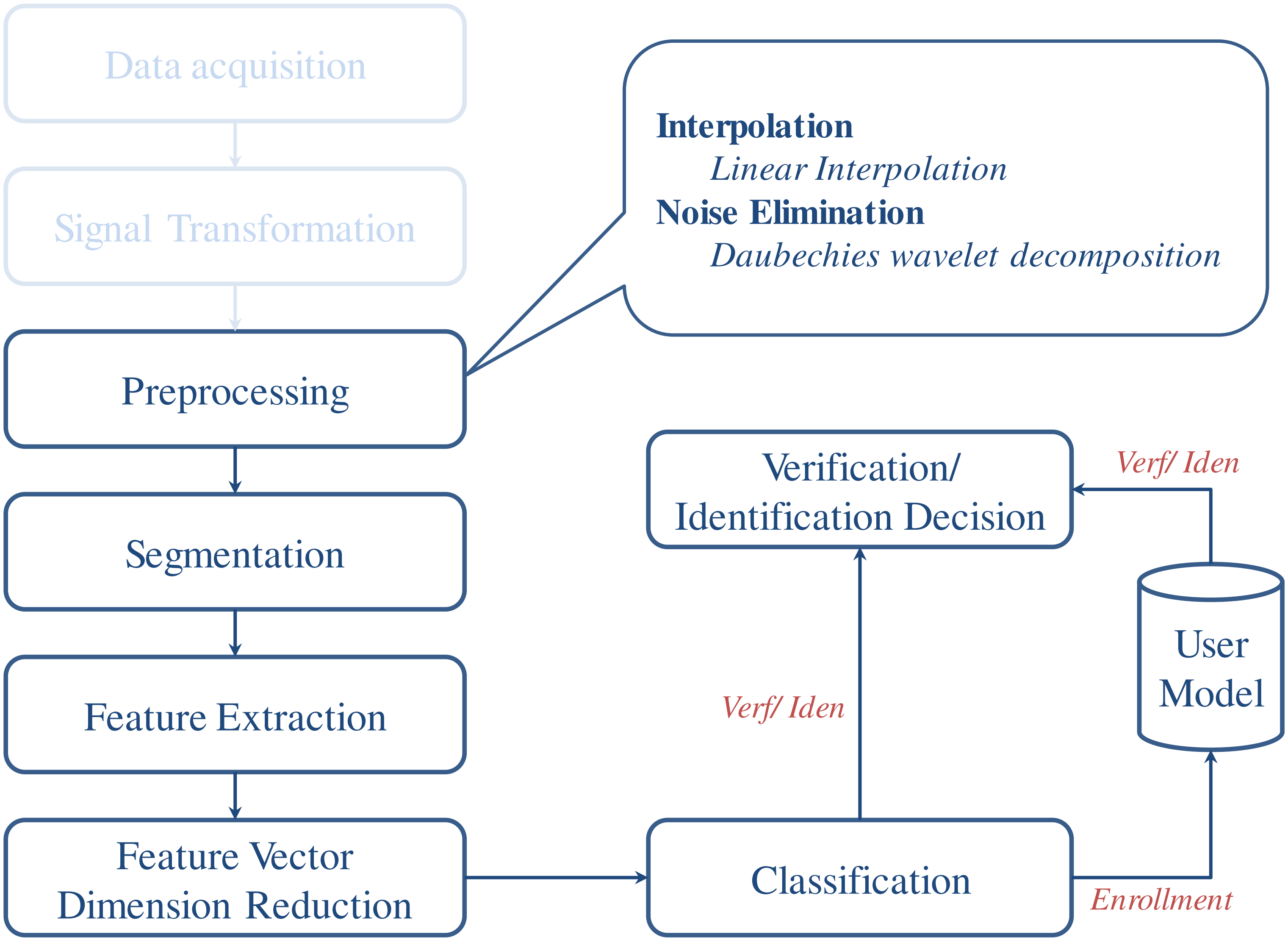
$$\mathbf{a}^{(XY)} = (a_1^{(XY)}, \ldots, a_i^{(XY)}, \ldots, a_n^{(XY)}) \quad , \quad \mathbf{a}^{(M)} = (a_1^{(M)}, \ldots, a_i^{(M)}, \ldots, a_n^{(M)})$$

where $a_i^{(XY)} = \sqrt{(a_i^{(X)})^2 + (a_i^{(Y)})^2}$, $a_i^{(M)} = \sqrt{(a_i^{(X)})^2 + (a_i^{(Y)})^2 + (a_i^{(Z)})^2}$

Finally, the gait signal after transformation will be presented in 3 dimensions which are ***immune*** to the disorientation of the sensor

$$\mathbf{A} = \left[\mathbf{a}^{(Z)} \;\; \mathbf{a}^{(XY)} \;\; \mathbf{a}^{(M)}\right] = \begin{bmatrix} a_1^{(Z)} & a_1^{(XY)} & a_1^{(M)} \\ \vdots & \vdots & \vdots \\ a_i^{(Z)} & a_i^{(XY)} & a_i^{(M)} \\ \vdots & \vdots & \vdots \\ a_n^{(Z)} & a_n^{(XY)} & a_n^{(M)} \end{bmatrix}$$

ML-Based Gait Recognition Model



Segmentation

Gait cycle-based segmentation

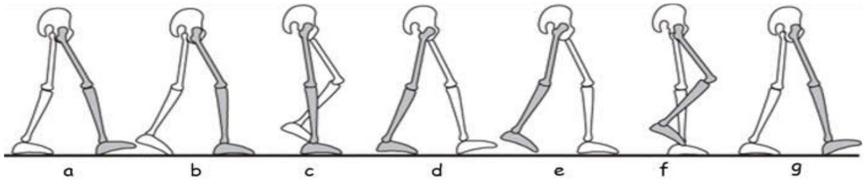
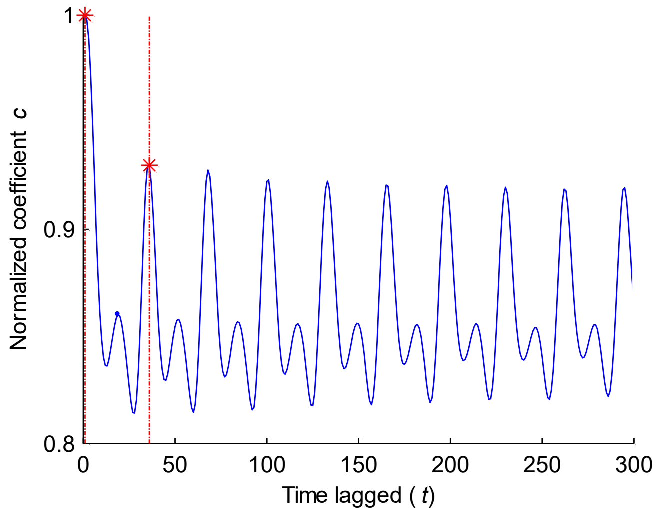
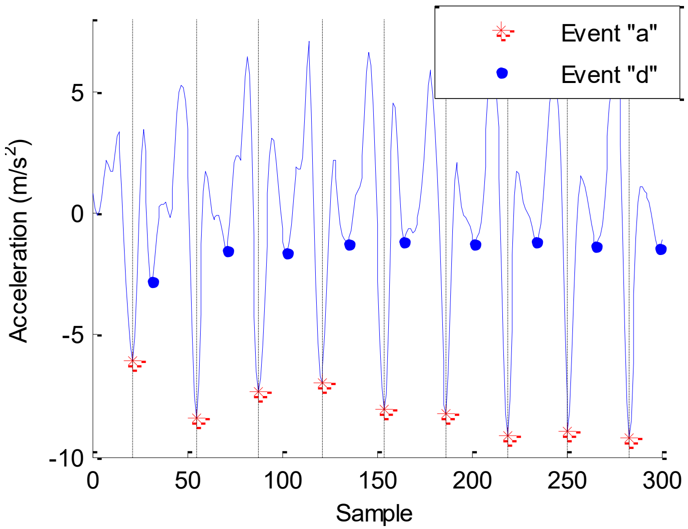


Fig. 4. Illustration of a gait cycle

According to two criteria: acceleration magnitude and the length of each gait cycle



Autocorrelation coefficients $c_t\,(0 \le t < n)$ of the $Z-$dimension signal

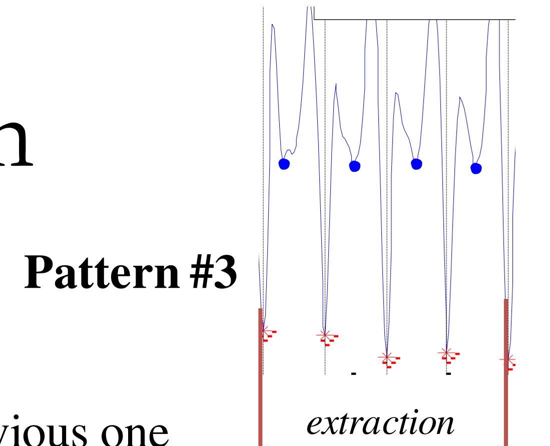


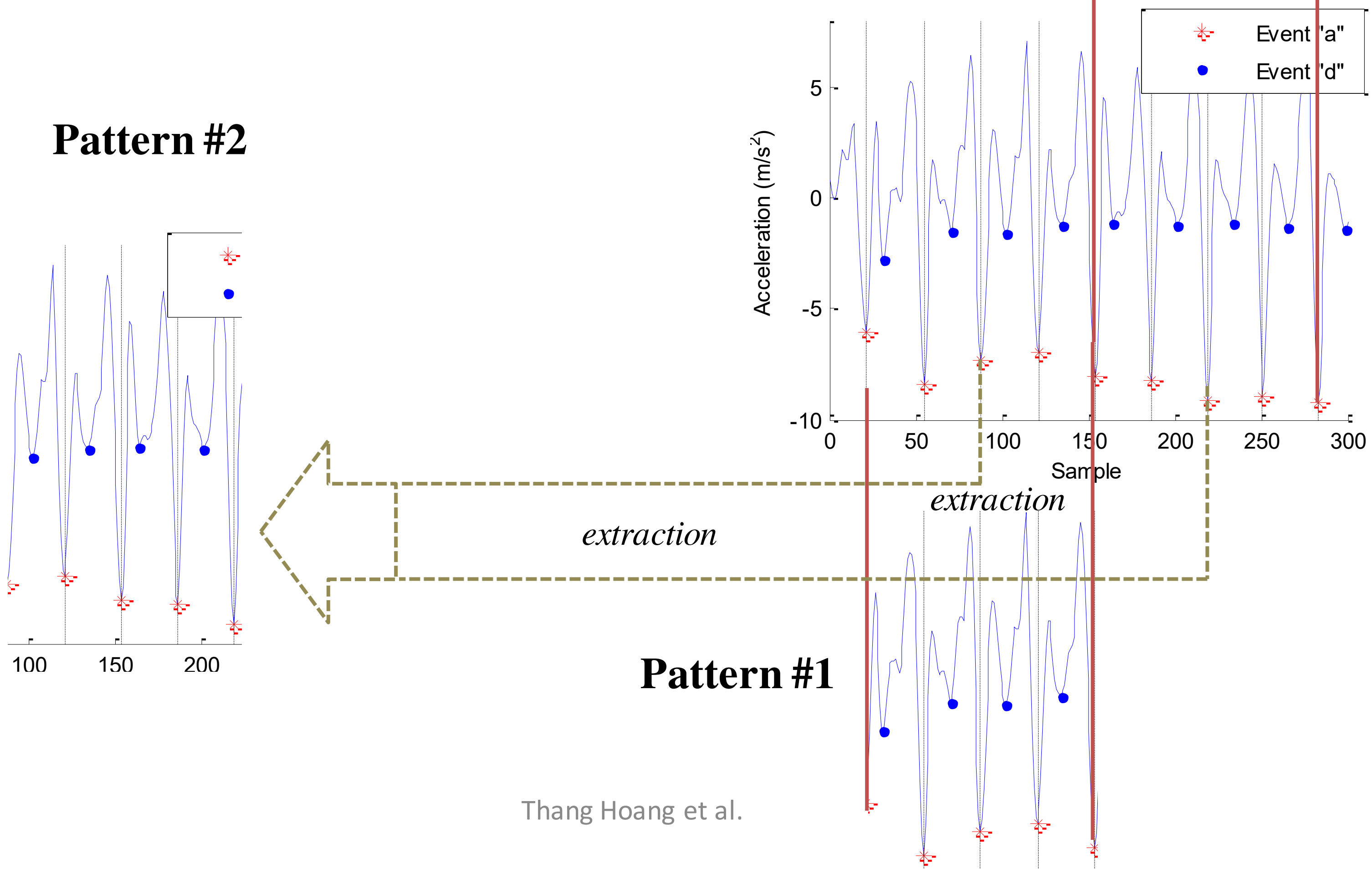
Detected marking points in $Z-$dimension signal

Segmentation

Gait Pattern Extraction

4-gait-cycle segments, overlapped 50% with the previous one





Feature Extraction

Time domain: *Statistical analysis*

- Mean of the max/min value;
- Average absolute difference;
- Root mean square;
- Standard deviation;
- waveform length;
- 10-bin histogram distribution;
- Average length of gait cycles

Frequency domain

- Magnitudes of first 40 FFT coefficients
- First 40 DCT coefficients

Feature Vector Dimension Reduction

Objective

Increase the learning time while maintaining the discriminability of the gait feature vectors

→ *Lighten the system to make it runnable on constraint devices*

Principal Component Analysis (PCA)

- The length n of the PCA-ed feature vectors is selected such that first n eigenvectors must capture at least 99.5% of the total variance.
- $n = 42$ for the dataset used in this study.

Classification

Two schemes:

- Template matching: PCA
  - PCA-ed feature vectors are stored in the mobile storage for matching.
- Supervised learning: SVM+PCA
  - Support Vector Machine (SVM) supervised learning: build the gait model.
  - libsvm opensource[1]: simulate SVM learning and prediction.

[1]Download available at https://www.csie.ntu.edu.tw/~cjlin/libsvm/

Experimental results

Configurations

- **Dataset:** 38 subjects
- **Recording device:** Google Nexus One, **sampling rate:** 27 Hz
- **# of gait patterns extracted:** 10,000+

- Re-implement related works [2-4] for evaluating the solution for disorientation problem and comparison to the proposed machine-learning approach

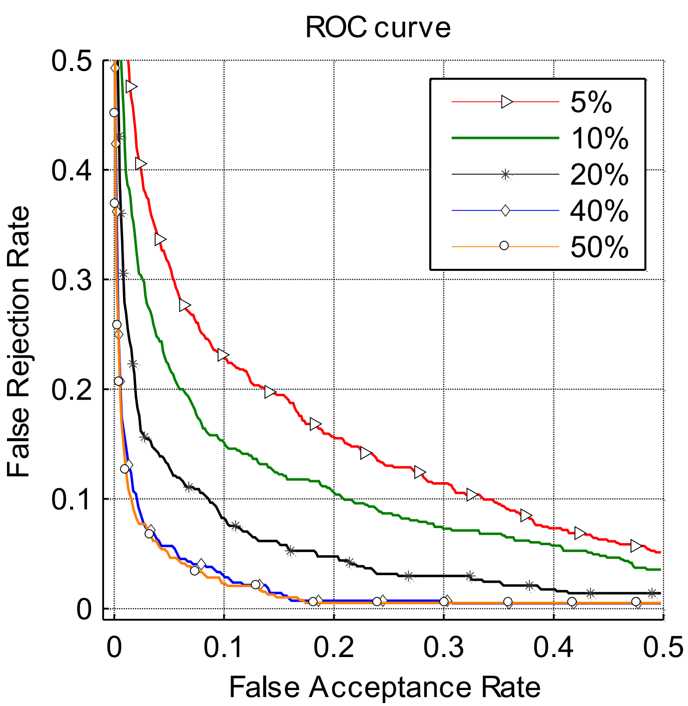
The configuration differences in between the original study and this experiment

Method	Original setup				This experiment			
	Axes	# Subject	Position	SR (%)	Axes	# Subject	Position	SR
Rong et al.	X,Y,Z	38	Ankle	250	Z,XY,M	38	Front pocket	27
Gafurov et al.	Z	30	Ankle	100	Z	38	Front pocket	27
Derawi et al.	M	60	Hip	100	M	38	Front pocket	27

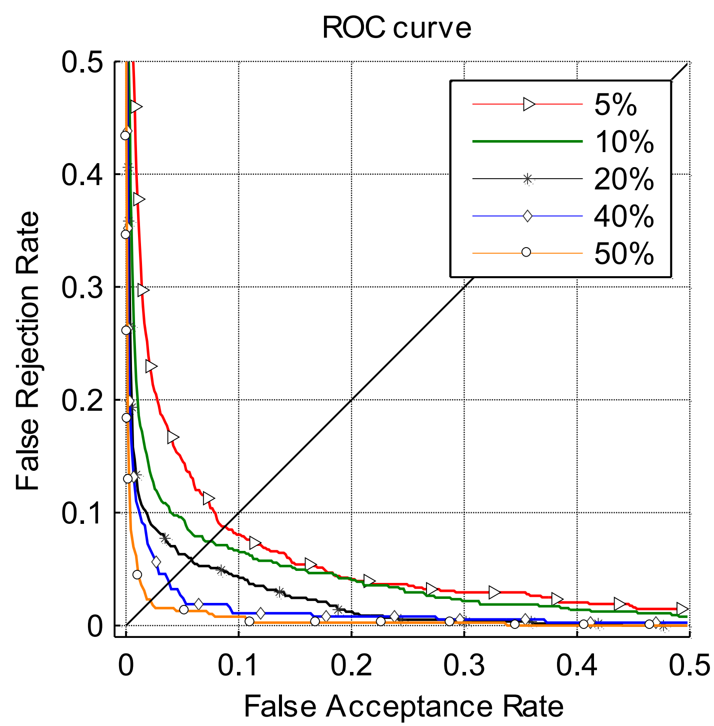
Experimental results

Verification results

With different proportion of training/ testing data



PCA

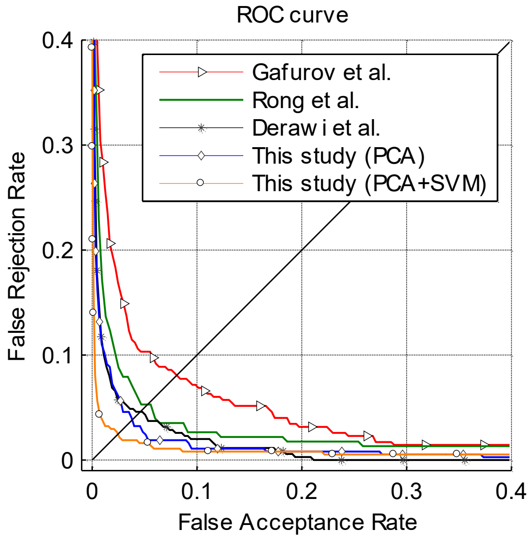


SVM+PCA

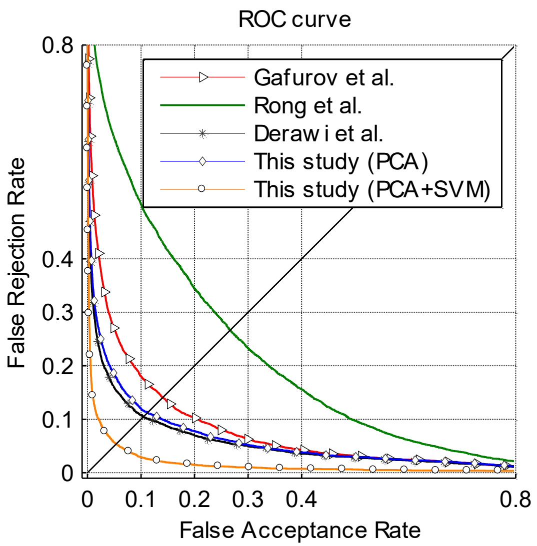
Experimental results

Verification results

Compare with other related works



Session-based verification



Pattern-based verification

Method	Session-based			Pattern-based	
	EER(%) (*original*)	EER (%)	FRR (%) (*at* FAR = 1%)	EER (%)	FRR (%) (*at* FAR = 1%)
Rong et al.	5.6	5.28	16.47	26.67	84.27
Gafurov et al.	2.2 – 23.6	8.07	28.43	14.11	52.37
Derawi et al.	5.7	4.59	10.71	10.49	31.86
Proposed method (PCA)	–	3.83	10.75	11.23	35.03
Proposed method (PCA+SVM)	–	**2.45**	**3.75**	**5.35**	**14.38**

Experimental results

Verification results

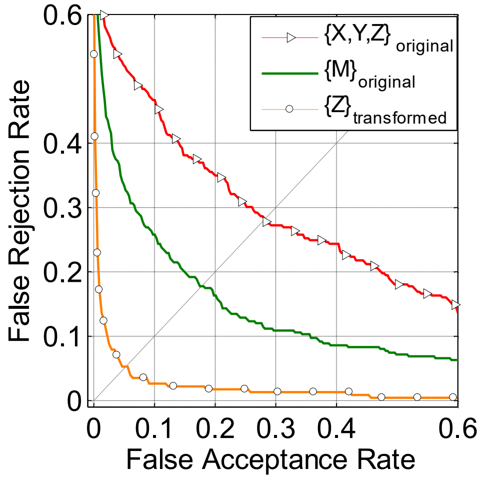
Compare with other related works

- *k-NN is used to perform identification for all schemes, except the SVM+PCA scheme*

Method	Accuracy rate (%)	
	Session-based	Pattern-based
Rong et al. (+kNN)	93.12	64.82
Gafurov et al. (+kNN)	87.68	76.55
Derawi et al. (+kNN)	93.41	88.09
Proposed method (PCA+kNN)	96.56	85.48
Proposed method (PCA+SVM)	**99.14**	**94.93**

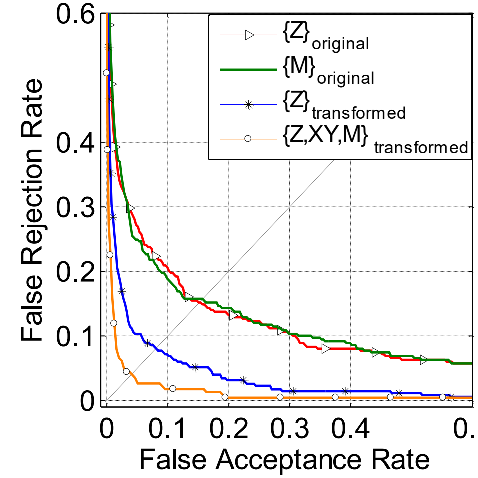
Experimental results

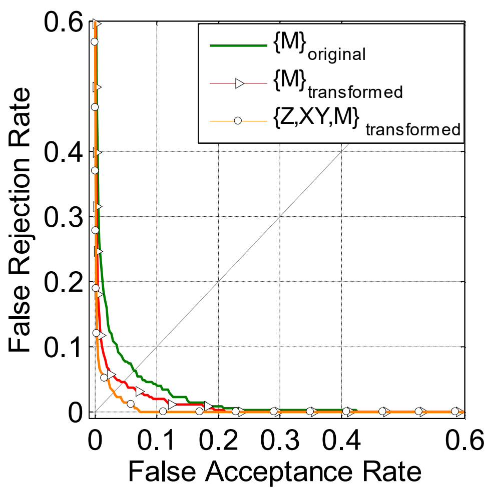
The impact of disorientation error



Rong et al.

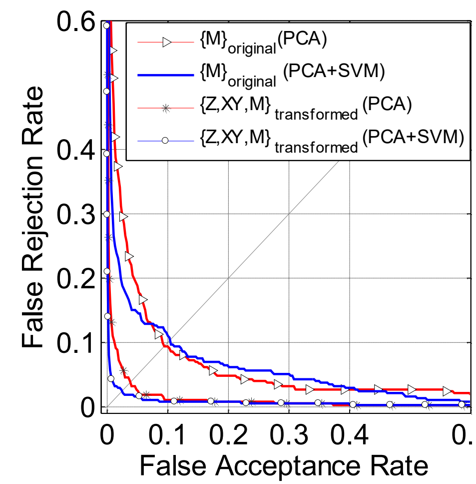
Gafurov et al.





Derawi et al.

The proposed method



Conclusions

- Addressed the sensor disorientation problem

  Not only useful for gait authentication but also effective for applications using 3D acceleration signals (activity recognition, fall detection, etc.)

- Proposed an machine-learning based gait recognition scheme

Drawbacks!

- The phone location is not flexible.
- Potential vulnerability: User gait model and templates are stored insecurely in mobile storage (***critical!!!***).

Current & further works

- Independent location of the device.
- Biometric gait template protection

References

1. Ailisto, H. (2005). Identifying people from gait pattern with accelerometers. In *Defense and Security*. SPIE.
2. Derawi, M. et al. (2010a). Improved cycle detection for accelerometer based gait authentication. In *In Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP)*. IEEE.
3. Gafurov, D. et al. (2010). Improved gait recognition performance using cycle matching. In *Advanced Information Networking and Applications Workshops (WAINA), 2010 IEEE 24th International Conference on*. IEEE.
4. Rong, L. et al. (2007). A wearable acceleration sensor system for gait recognition. In *Industrial Electronics and Applications, 2007. ICIEA 2007. 2nd IEEE Conference on*. IEEE.

Q&A

Thanks for listening!

Question?