FootprintID: Indoor Pedestrian Identification through Ambient Structural Vibration Sensing

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Outline

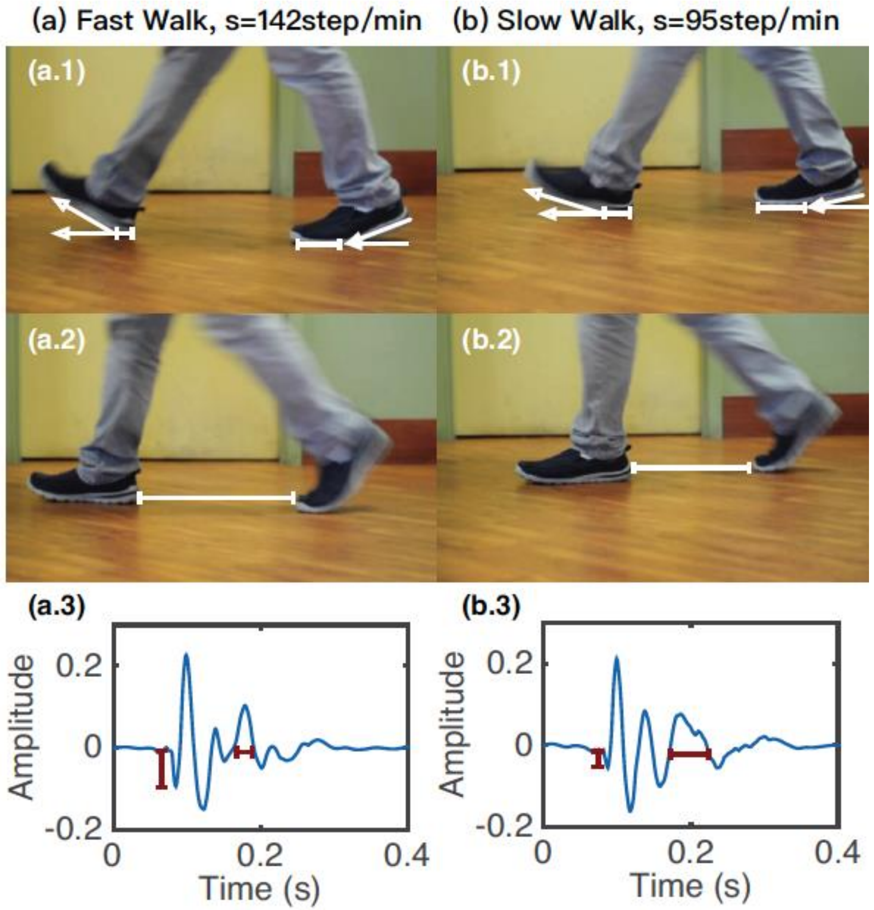
- Introduction
- System Design and details
- Evaluation
- Conclusion

Introduction: *FootprintID*

- Identify a pedestrian through the footstep-induced vibration on the floor
  - ***The unique walking patterns induce distinguishable vibration***
  - It should consider the sensitivity to changing walking conditions including walking speed and stepping locations
- Present a novel algorithm to infer pedestrian identity
  - Select step signals based on stepping location
  - Select supervised or transductive classifiers based on walking speed
  - Apply RTSVM and ITSVM when the tested walking speeds vary from those in the labeled training set

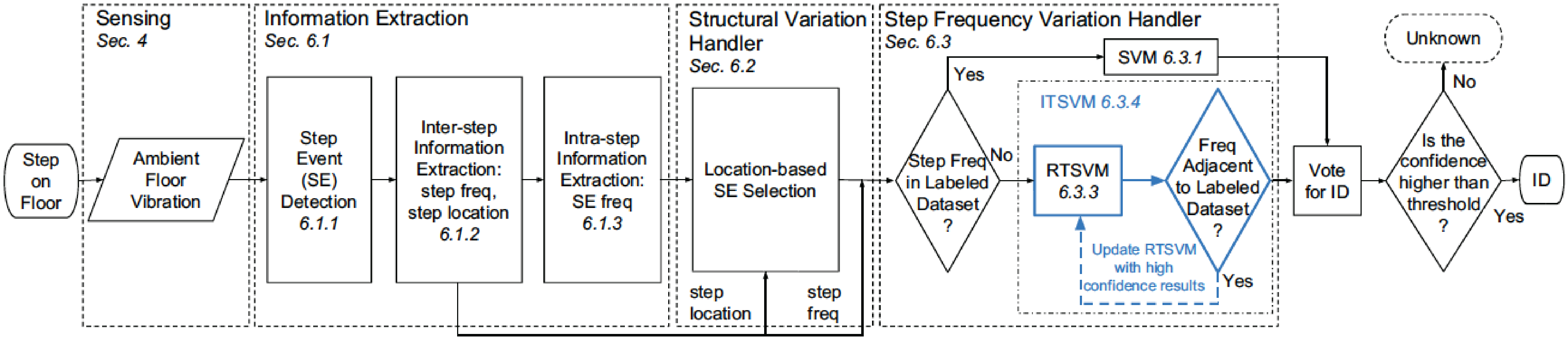
Background: Vibration from Gaits

- Why people have different gaits
  - Gait describes a subject's walking pattern including limb locomotion and neurological control
- Why the location and frequency of the steps affect the sensing signal
  - Vibration signal waveforms can be different due to material heterogeneity and structural layout
  - The higher the step frequency, the longer the step length, and the faster the walking speed



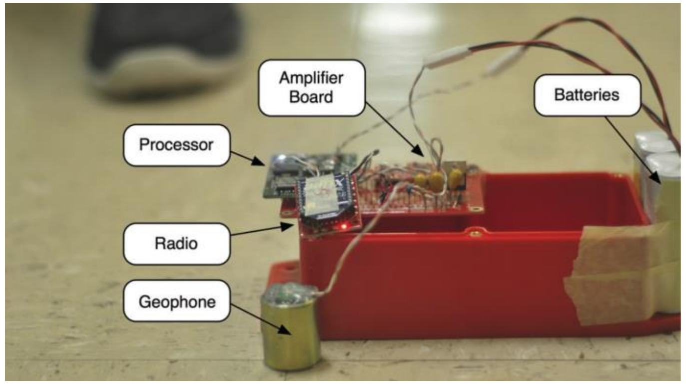
System Overview

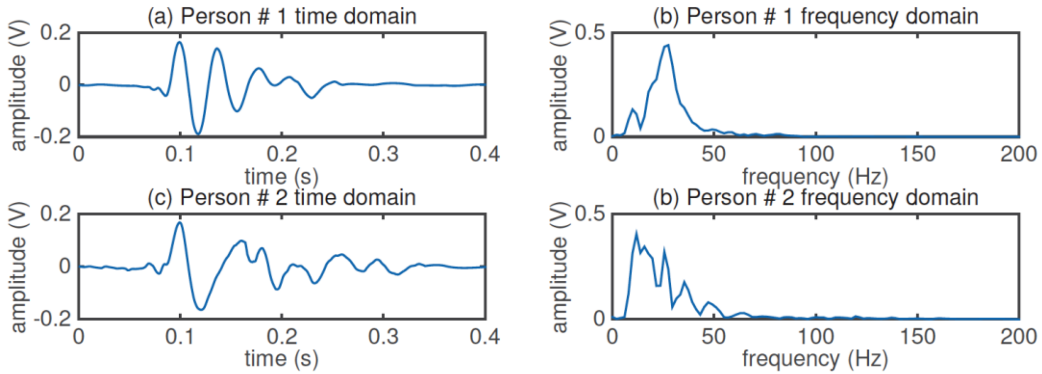
- Identify pedestrians by classifying gait patterns
  - Gait patterns would be distinguishable based on each person's walking habits
- Need to overcome variations due to structural difference of each floor and step frequency variation by walking speed



1. Data Sensing

- Place a sensing unit on the floor and fix geophone to preserve high-frequency signals
- Convert the velocity of the monitored surface to voltage by geophone
- Convert the signal into a digitized signal with a 10-bit ADC module sampled at 1000 Hz
- Observe a clear difference in both time and frequency domains of different gaits from two pedestrians



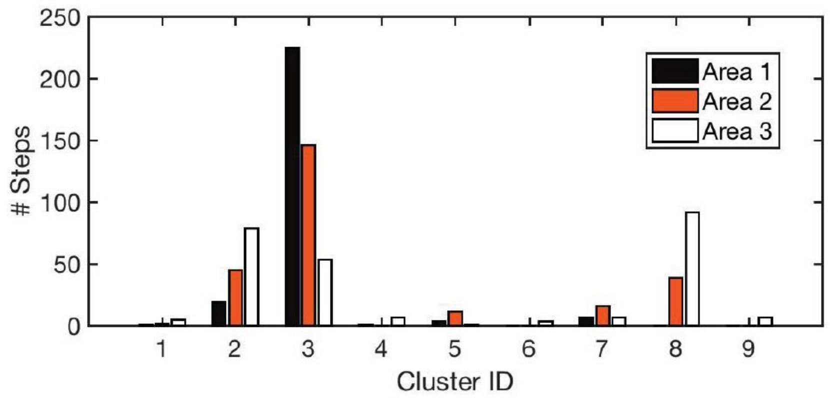


2. Information Extraction

- Conduct feature extraction to represent a person's footstep effectively
- Step Events Detection → $\boldsymbol{threshold = \mu_{wse} + 3\sigma_{wse}}$
  - Form a Step Event by finding consecutive candidate windows which have higher energy value over the threshold
- Inter-footstep step frequency and relative location
  - Estimate the average time interval between consecutive Step Events excepting the highest and lowest K values
- Intra-footstep frequency
  - Normalize the signal energy to remove the footstep-sensor distance difference

3. Structural Vibration Handler

- Should select SEs that are from approximately the same area from each trace
  - Even similar foot strikes are only comparable when they are from the same area



- Infer step location based on the SE of the closest area to the sensor to overcome structural variation
  - Calculate the average value of SE energy using a sliding window to smooth the trend change
  - Select the peak of the sequence of calculated value as the closest area to the sensor

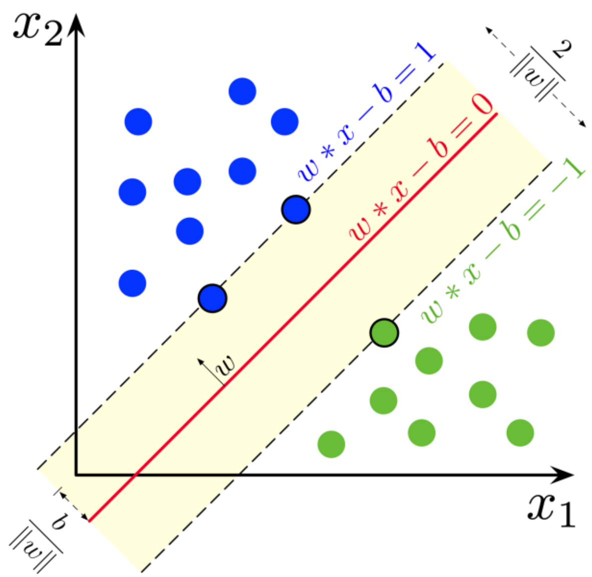
4. Step Frequency Variation Handler

- Aim to acquire better accuracy, even though a large amount of labeled training data is not collected from diverse walking speeds

→ Accuracy vs. Performance

- Choose between supervised learning and transductive learning based on the detected footstep step frequency
  - Apply the supervised learning model (SVM) directly for a dataset with step frequencies in the labeled training data
  - Use an iterative transductive support vector machine (ITSVM) algorithm if the step frequency is not in the labeled training data

Support Vector Machine (SVM)



- Find the maximum-margin hyperplane w by minimizing the loss function, given two-class training data

$$\min_{\boldsymbol{w}, b} \quad \frac{1}{2}||\boldsymbol{w}||^2 + C\sum_{q=1}^{l} \max(1 - y_q(\boldsymbol{w}^T\phi(\boldsymbol{x}_q) + b), 0),$$

  - Balance regularization term and training losses

- Achieve high accuracy in identifying the participants when they walk at a specific speed during a short amount of time

→ How about different step frequency?

References: https://en.wikipedia.org/wiki/Support-vector_machine

Transductive SVM (TSVM)

- Find the maximum-margin hyperplane *w* and bias term *b* by minimizing the following loss function, given two-class training data and unlabeled data

$$\min_{\boldsymbol{w},b} \quad \frac{1}{2}||\boldsymbol{w}||^2 + C_1 \sum_{q=1}^{l} \max(1 - y_q(\boldsymbol{w}^T\phi(\boldsymbol{x}_q) + b), 0)$$
$$\boxed{+ C_2 \sum_{q=l+1}^{l+u} \max(1 - |\boldsymbol{w}^T\phi(\boldsymbol{x}_q) + b|, 0),}$$

- Tend to find boundaries in regions where there is less labeled and unlabeled data (low-density separation method)

→ How about reducing irrelevant unlabeled data?

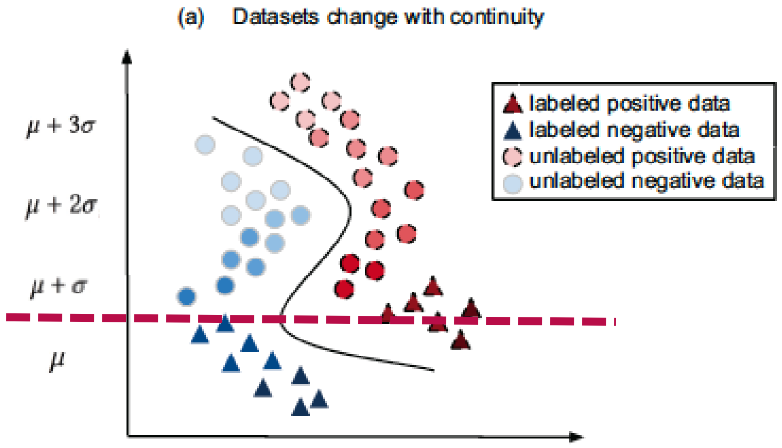
Refined Transductive SVM (RTSVM)

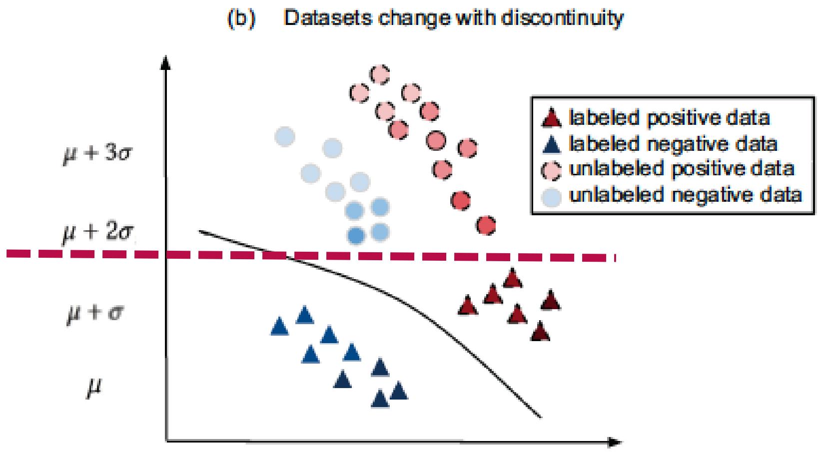
- Need to refine the relevant unlabeled data for the training of each binary TSVM to overcome the irrelevant unlabeled data problem → *k-class problem*
  - A selected unlabeled dataset leads to a faster training speed
- Utilize supervised SVM to pre-select unlabeled SEs, which are most likely to be class i or j
  - Use multi-class SVM with labeled data to predict the identity of all unlabeled SEs
  - Calculate the most frequently appearing class in each trace as the class of the trace and use SEs for the binary TSVM modeling

→ How about various step frequencies?

Iterative Transductive SVM (ITSVM)

- Train multi-class TSVM model in an iterative way
  - Label some unlabeled data in the frequency of $\mu \pm \sigma$ to increase the size of the 'labeled' dataset
  - Construct multi-class RTSVM with the test data with step frequencies of $\mu \pm 2\sigma$ and $\mu \pm 3\sigma$ based on the updated labeled dataset

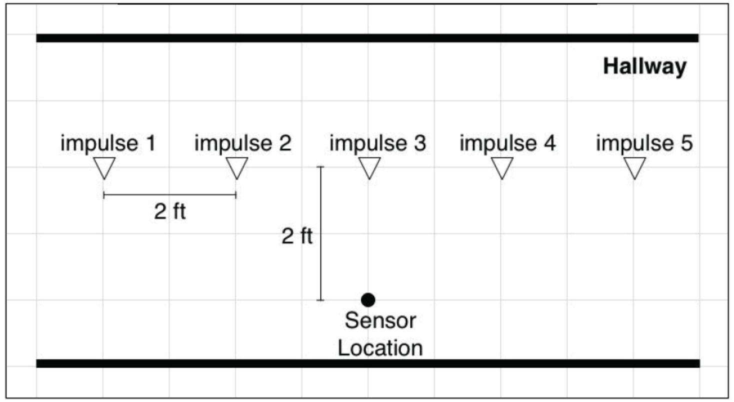




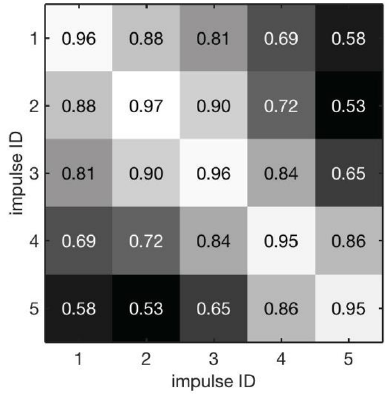
Load Test

- Figure out the reasonable threshold to cluster the Step Events indicating negligible differences caused by structural variation
  - The load test uses ball drops to understand structural vibration without human behavior randomness
  - The structural variation effects on footstep induced vibration data can be clearly observed in the area monitored by one sensor

(a) Load test experiment deployment



(b) Impulse similarity comparison (xcorr)

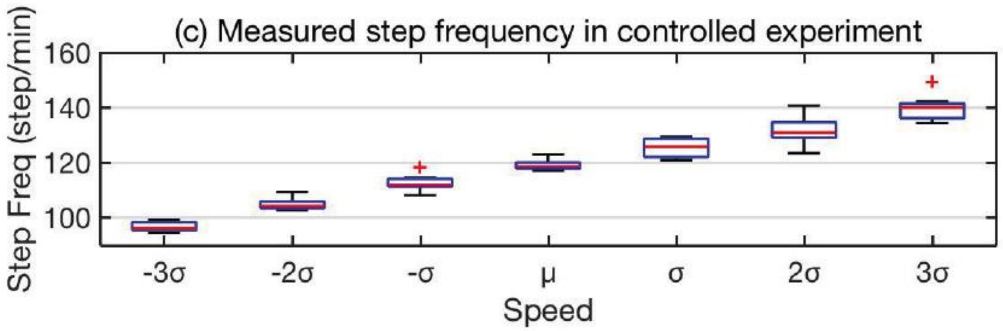


Controlled Human Test

- Collect data for seven controlled step frequencies with metronome beats

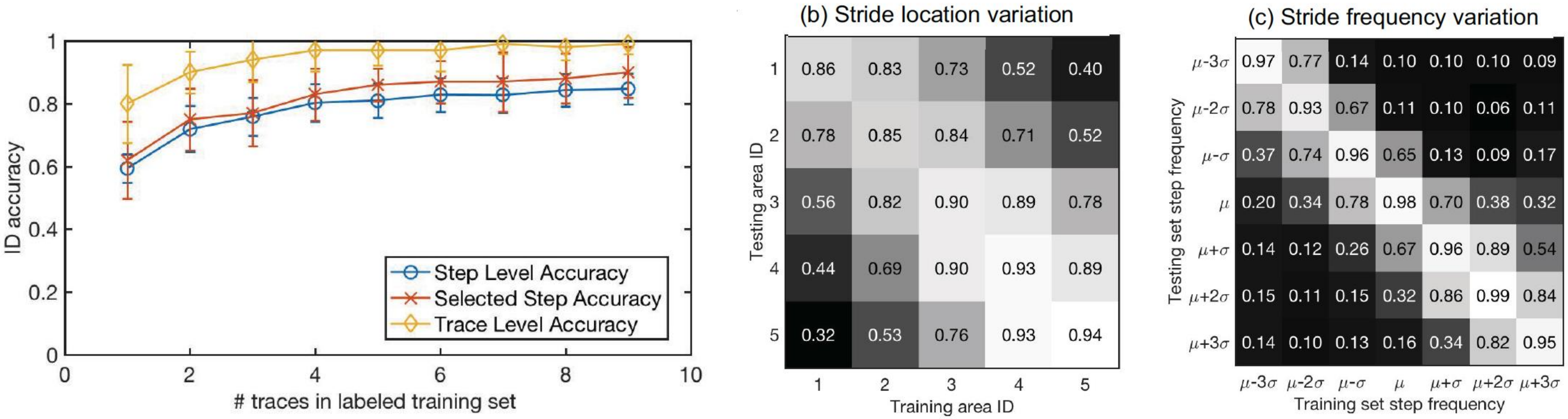
Gender \ Step Freq	$\mu - 3\sigma$	$\mu - 2\sigma$	$\mu - \sigma$	μ	$\mu + \sigma$	$\mu + 2\sigma$	$\mu + 3\sigma$
Male	95	103	111	119	127	134	142
Female	98	107	116	125	134	143	152

- Consider various step frequency due to randomness in human behavior
  - Check that the variations are small enough and each level is clearly distinguishable



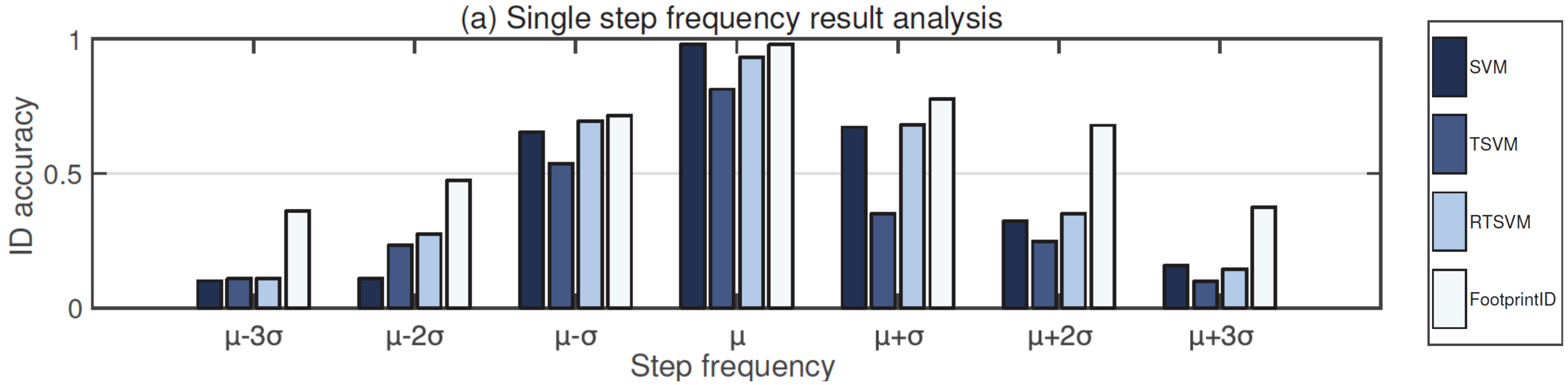
Evaluation of System Factors

- Compare the effect of the amount of labeled training dataset, step location, and step frequency to identification accuracy



Algorithm Analysis

- Evaluate the identification accuracy and runtime for scalability using SVM, TSVM, RTSVM, and ITSVM

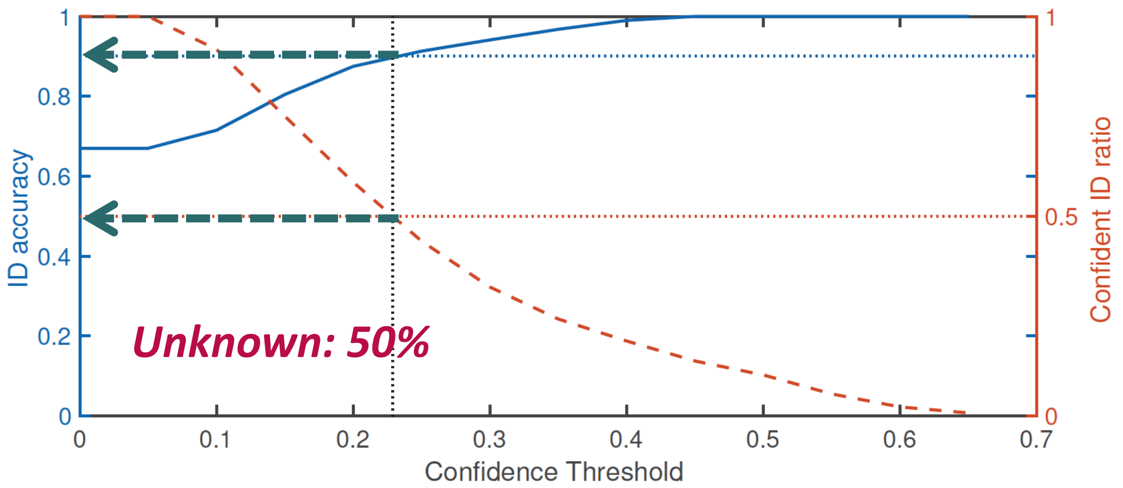


Algorithms	SVM (train on μ)	SVM (train on $\mu \pm 3\sigma$)	TSVM	RTSVM	ITSVM (FootprintID)
Runtime Avg. (s)	0.8724	9.7886	382.4303	74.7586	218.9920
Runtime Std. (s)	0.0496	0.9174	94.8886	8.3837	18.9385

Uncontrolled Experiments

- Evaluate the system based on pedestrian's natural walking form
- Achieve the best accuracy due to the higher accuracy on the low step frequency data in case of ITSVM
- Improve identification accuracy from 67% to 90% when threshold discards half of the data

Models	SVM	TSVM	RTSVM	ITSVM (FootprintID)
labeled: μ, unlabeled: $\mu \pm \sigma$, $\mu \pm 2\sigma$, $\mu \pm 3\sigma$, uncontrolled	56%	52%	52%	67%
labeled: μ, unlabeled: $\mu \pm \sigma$, $\mu \pm 2\sigma$, $\mu \pm 3\sigma$	56%	54%	51%	67%
labeled: μ, unlabeled: uncontrolled	50%	22%	22%	45%



Conclusion

- Present the **FootprintID** system which identifies pedestrians using footstep induced structural vibrations
- Characterize the variation of footstep induced structural vibration signals and design ITSVM learning algorithm
- Identify correct pedestrians up to 96% accuracy by ITSVM with the average step frequency μ dataset as training data
- Demonstrate to improve 1.5X identification accuracy in uncontrolled experiments based on ITSVM

Thank you