Nonintrusive Occupant Identification by Sensing Body Shape and Movement

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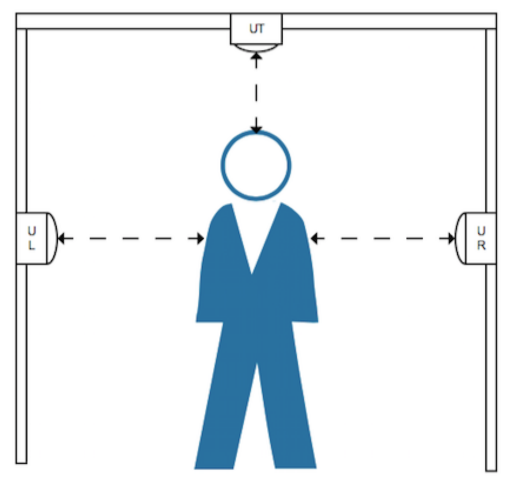
Introduction

Indoor identification has numerous applications:
- Smart buildings to customize climate according to occupants
- Customer behavior analysis

We present a nonintrusive method to identify occupants by sensing occupants' body shape and movement using 3 ultrasonic sensors attached to a door frame.
We are able to identify occupants with an accuracy of 95% within a group of 20 people.

Competing methods use:
- Wearable gadgets [1,2]
- Smartphones [3]
- Footstep vibration [4,5]
- One ultrasonic sensor for measuring height [6]



Methodology

A. Sensing and calibration

Each door frame is composed of 3 ultrasonic sensors:
UT (top), UL(left), UL(right)
UL and UR are displaced to avoid crosstalk
We measure delay the beam sending and reception
We convert delay to distance
Convert measure to height and width
dheight(tUT) = dmaxheight − 34.3 tUT
dwidth(t)=dmaxwidth−34.3tUL−−34.3tUR
34.3 is the distance traveled by sound in 1ms

B. Walking pattern Recognition

We sample at 35 Hz.
Each time a person walks, we generate a stream of data
We use height to detect if a person passed the door.
We detect the direction of the walker using the UL,UR displacement

C. Noise Canceling and correction

Identify noisy points and recover them using linear interpolation

D. Feature extractioon

From the data stream, we extract a set of features to summarize the walking event

1. Girth

This represents the person's waist circumference

Algorithm 1 Girth Calculation Algorithm

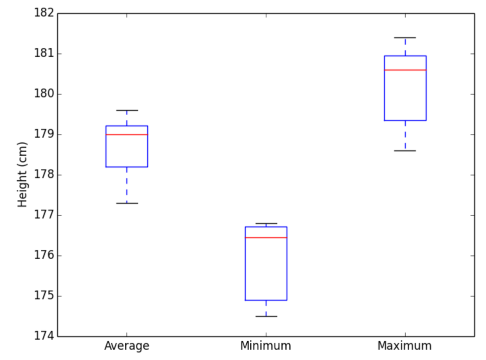
procedure COMPUTE GIRTH
  edge ← 0
  loop: t = 1 ... n
    $x_t \leftarrow \frac{width[t]}{2}$
    $y_t \leftarrow iteration_t * distance\_walked\_per\_iteration$
    $edge \leftarrow edge + \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$
  Return: *girth* ← 2 * edge
end procedure

2. Time

We measure the time spent walking under the door

3. Maximum, Minimum and Average height and width

Average height even if not the closest to the ground truth is most consistent and best feature to use



4. Bounce

Difference between max and min height

5. Body-hand distance

How far the hands are from the body when walking?

E. Occupant Identification

We use DBSCAN to build a cluster for every person using the feature pair (girth, time) to represent a walking event.

Evaluation

A. Testbed

We used 3 Parallax ultrasonic ping sensors, Arduino Uno and raspberry PI. We used a logitech C310 camera for ground truth.
We sample at 35 Hz and we sense sequentially with order UT→UL→UR.
The displacement of 1.2cm between UL and UR has been chosen taking into consideration an assumed speed of 5 Km/h.

B. Experimental Setup and Ground truth

We conducted an experiment for 1 month in Building T2 room 218
Participants were encouraged to walk naturally, we captured a video for every walking event.
Each time a participant walked, we captured the data stream.
53 people participated, but we decided to take the top 20 in terms of number of walking events. This group averaged 7.5 events per person, with 11 males and 9 females.

C. Evaluation metrics

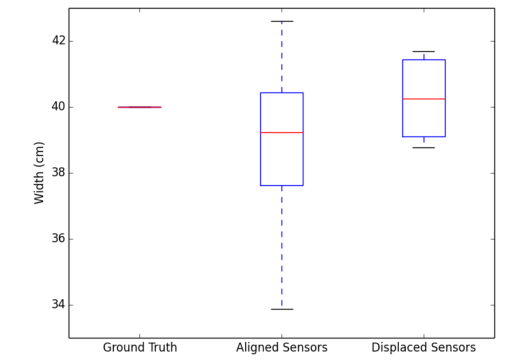
We used clustering to identify people. We used 2/3 as training dataset and 1/3 for testing.

TABLE I: Different outcomes from clustering

	Same cluster	Different cluster
Same Person	True Positive (TP)	False Negative (FN)
Different Person	False Positive (FP)	True Negative (TN)

D. Width measurement evaluation

The goal is to evaluate if the displacing UL and UR is the best way to sense the width.



D. Clustering with a single feature

Can we cluster with 1 feature and identify with high accuracy?
We built a clustering model for every single feature.

TABLE II: Accuracy achieved by clustering using different features.

Feature	Accuracy
Average Height	84.3%
Bounce	88.1%
Average Width	87.6%
girth	89.5%
Time	82.6%
Waist-hand distance	76.9%

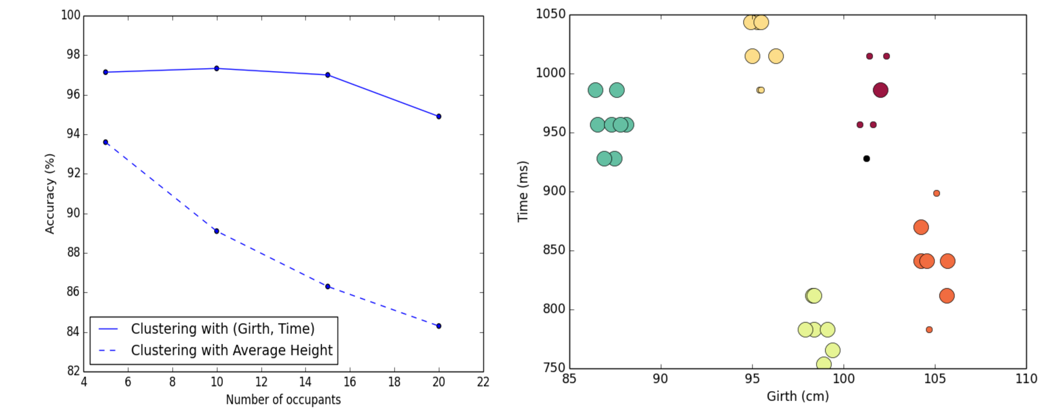
E. Clustering with pairs of features

TABLE III: Accuracy achieved by clustering with composite features constructed from the features in row and column.

	Height	Width	Bounce	Time	Girth	WH
Height	84.3%	89.5%	89.5%	90.5%	93.2%	86.4%
Width		87.6%	90.5%	91.0%	93.7%	87.2%
Bounce			88.1%	87.6%	94.7%	89.4%
Time				82.6%	95.4%	85.2%
Girth					89.5%	90.3%
WH						76.9%

F. Accuracy as a function of number of occupants

Accuracy decreases as a lower rate compared to other methods using height only



Challenges

Multiple entries: The current system expects only one person at a time
Higher number of users: The accuracy falls with the increasing number of users, but different feature pairs fail at different instances and we can combine them
Impact of belongings: A person carrying a bag of a purse will bias the data
Impact of walking patterns: The deta stream length is impacted by the speed. In normal behavior, people tend to walk at consistent speeds
Low power sensing: Current system is in constant polling which is energy intensive. We suggest adding a motion sensor to trigger the system when a person is close.

Conclusion

We introduce a system that nonintrusively identify occupants.
We achieve an accuracy of 95% with a group of 20 people
Girth combined with time is the best way to identify people
Bounce is a better way than average height to measure height for the purpose of identification

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