The Carpet Knows: Identifying People in a Smart Environment from a Single Step

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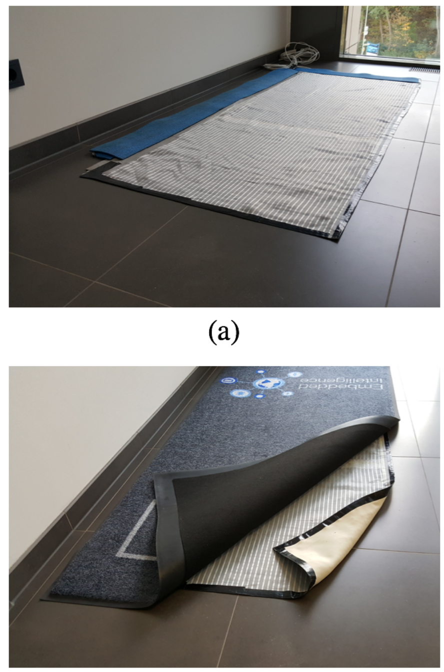
***Abstract*—In this paper, we present an approach for person identification using morphing footsteps measured from a fabric-based pressure mapping sensor system. The flexible fabric sensor is 0.5 mm thin and operates under a 5 mm thick normal carpet; therefore, it can be easily implemented into modern smart living spaces. We extract features concerning single steps with the shifting of gravity center, maximum pressure point and overall pressed area, which are independent from shape details and inter-step relationships of the walking sequences. The system is evaluated with 13 participants wearing shoes and walking normally across the carpet. Overall 529 footsteps are recorded, and the resulting average identification accuracy is 76.9%. Our approach can also be used for further activity recognition with the same physical carpet sensors.**

***Index Terms*—smart living space; gait analysis; pressure sensing matrix; person identification.**

I. Introduction

The development of pervasive computing, IoT, sensing and controlling systems have enabled traditional living spaces to have smart functionalities. By combining the input of environmental and user activity information with intelligent algorithms, activation mechanisms and information feedbacks, smart living spaces bring up the benefits such as improved convenience and experience for the users [1], optimized power efficiency [2], better understanding of the facility usage[3], elderly telemonitoring [4], etc.

In certain occasions, it is important to understand who is using the smart living space, therefore, occupants counting, tracking or identification is an important aspect of designing such smart environment systems. Occupants awareness opens up possibilities such as bringing personalized preferences into the smart space, user-focused dynamic reconfiguration of the environment settings, better energy management [5] or crowd analysis [6]. On the other hand, privacy intrusion is a major concern when investigating user awareness methods, since some certain instrumentation could gather information that the occupants are not willing to show. Walking gait is a major branch of person tracing or identification study, which can be recorded from either video or floor planar pressure (footprints). Especially, floor based instruments are less obtrusive and generally receive better acceptance.



(a)

(b)

Fig. 1. Sensing hardware: (a) the fabric sensor without cover; (b) the sensor can operate under normal carpets and be rolled up easily.

Therefore, we propose a system that detects the user identity by single footsteps without inter-step information from consecutive steps while the person is walking as usual without any instrumentation-induced distractions. The system is also very easy to be carried around and installed/uninstalled into any living spaces to enable such person identification capability to the environment.

A. Paper Contribution

In this study, we look into the footprints of the people and study not as static "ink-prints", but as the dynamic morphing sequences of the footprint while the people are walking. While other previous studies have looked into the relationship between steps, such as the angle and stride, such parameters

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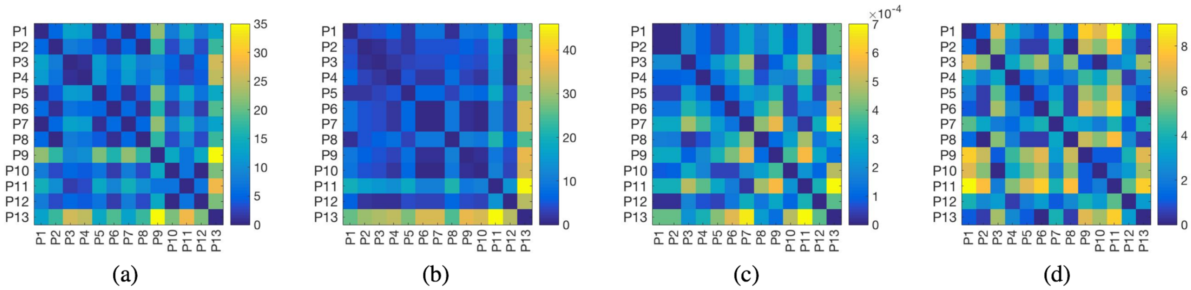

Fig. 2. Demographic difference distribution among participants, (a) height, (b) weight, (c) BMI, (d) shoe size. Yellow color indicates bigger difference.

may vary in a real world application, e.g. when the person walks faster or turns. Our contributions are as follows:

- Sensing carpet: we develop a system based on our previous system "Smart-Mat" [7], a fabric-based real-time pressure force mapping system, which can be easily integrated under a normal carpet. The mat tells us every 40 milliseconds how much pressure is applied on every 1.5cm on the floor area, making it possible to study the fast footprint change.
- Detecting person from individual steps: enabled by the hardware that has a scanning rate of 25 fps, we are able to extract information on a fine temporal resolution. We therefore ignore the inter-step geometrical relationships and look only into the changing of the footprint each time a foot is on the floor. We conducted an experiment with 13 participants, and achieved average accuracy of 77% with features extracted only from individual footsteps; the accuracy increases as the participant pool scales down.

While a majority of the systems from state of the art utilizes rigid or film-based sensors, our system design requires very flexible, light, non-permanent installation effort since the sensor is fabric based. It can be covered with standard carpets to be integrated into modern smart living spaces, and can be rolled up for storage and transportation.

B. State of the Art

In the discipline of pervasive computing, person identification has been investigated with various methods from close ranged facial, fingerprint, or barefoot planar pressure to further ranged activity-based vision, pervasive acoustic, planar pressure, etc. Biological cues can help identify person with high accuracy from even a large database. Such as the work by Brunelli, et al. [8] and Dieckmann, et al. [9] using combinations of multiple sources from voice and facial cues, from a database of 89 and 66 people, identification accuracy was near 100%.

However, in a smart living space, close range sensory that requires special user attention is not always desired, making gait analysis a popular approach. Gait analysis can be categorized into computer vision and planar pressure. Computer vision based gait analysis considers the visual movement of different body parts, and typically returns high accuracy [10] [11]; however there could be constraints such as viewing angles and space for the camera's view [12].

Planar pressure can be more suitable in narrow cramped spaces. With the users instructed to step onto a single-point weight scale that is continuously measuring, it is possible to detect the person from the dynamic footstep pressure change by the work of Orr, et al. [13]. A medical planar pressure mapping device is used and by analyzing dynamic high resolution barefoot footprint, Pataky, et al. has achieved 99.6% from 104 individuals [14].

However the high definition medical planar pressure mapping devices are cumbersome, costly and hard to scale-up to be implemented into pervasive smart environments. Yun has comprehensively summarized [15] several approaches that uses systems installed into floor or floor-mat. These approaches has less spatial resolution, and typically considers situations with socks or shoes, therefore, the resulting pressure mapping inherits less details from the users' foot and the typical accuracy is in the range of above 60% as shown in Fig. 7. Many of the approaches include re-installing the entire floor of the sensing area [16], or big coverage to capture a sequence of steps [16] [17] [18].

Except for planar pressure, capacitive floor mats for detecting the presence of people are also used for tracking the people's walking trajectory (Sousa, et al. [19]).

II. Study Setup

A. Hardware

The hardware is a variation of the sensing system in our previous study "Smart-Mat" [7]. The fabric sensor mat consists of top and bottom layers of parallel electrodes, which are metallic fibers woven into a non-conductive polyester substrate; and a middle layer of CarboTex, a carbonated polymer fabric; all three layers together measure at 0.5 mm thick. The fabrics are designed and manufactured by Sefar AG [20]. The top and bottom layers produce 120-by-54 pressure sensitive points, 1.5 cm away from each other. The mat therefore coves a 1.8m by 0.8 m area as shown in Fig. 1 (a), and a normal carpet is placed on top of the sensing mat. The sensing mat can be placed and removed on any floor without permanent installation efforts such as drilling or replacing the floor.

A custom designed data acquisition system, which implements our proposed architecture for largely scalable pressure

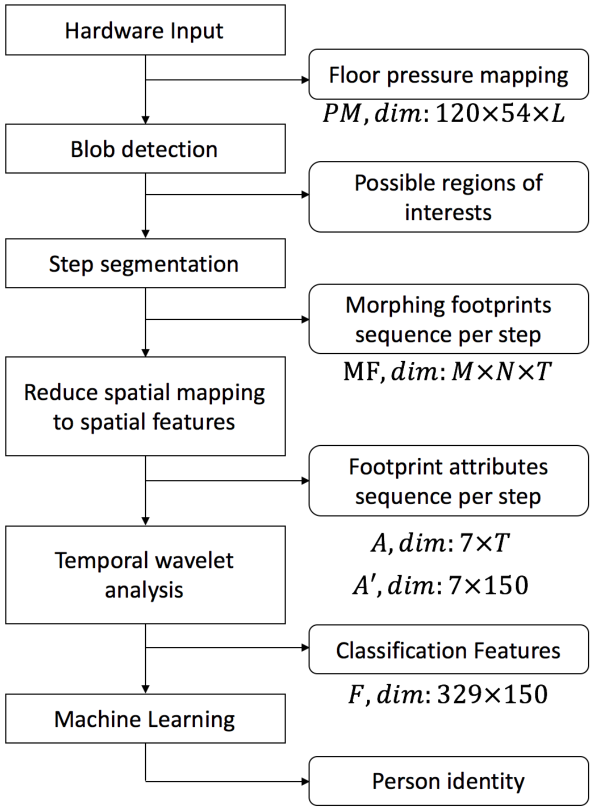

Fig. 3. Overall algorithm flow chart

mapping [21], drives the top layer with a scanning stimuli and measures the bottom layer for the individual pressure. The data is sent to the computer through a USB cable which also powers the system.

B. Experiment Design

To evaluate our system, walking patterns are recorded from a group of 13 people (11 males and 2 females) in the age group of 24-30 years. Each participant walks with their normal shoes on the pressure sensitive mat of at least 12 rounds. Participants are not bare feet while walking on the mat, however, they continue to wear the same footwear in all the repetitions. To account for the variance in the recorded data, it was ensured that the height, weight and shoe-size of the participants vary over a good range; which is from 155-195 (in cm), 64-100 (in Kg) and 37-45 (European size) respectively. We visualize the demographic distribution of height, weight, BMI and shoe size differences in Fig. 2 for detailed reference, brighter color means higher difference between two persons. During an experiment, it is not necessary to walk all the repetitions at once. The participants are free to take rest or do anything between the repetitions.

Each repetition is recorded as a separate dataset and labeled with the specific person. The ground truth of each repetition is annotated manually which includes the starting and the ending time frame for every step. Overall, 529 steps are recorded.

III. Evaluation

We focus our evaluation on identifying person from the morphing footprint of individual steps. As shown in Fig. 3, we first capture the steps through standard blob detection; then the spacio-temporal domain of the morphing footprint is processed through spatial computation and result in sequences of attributes of each state of the footprint; features are then calculated from wavelet analysis of the said attribute sequences; at last we perform cross-validation to evaluate how well the data can indicate the identity of the person.

A. Step Detection and Segmentation

The raw data is a temporal sequence of 120×54 2-spatial-dimensional pressure mappings. Fig. 4 (a) shows the original signal as a sum of PM in its time domain (similar to a "long exposure" in photography); every frame sample is a moment of the footprint such as those shown in Fig. 5. By computer vision methods, the spatial region of each step can already be detected from Fig. 4 (a); however, we need to segment the steps not only by the spatial region, but also by the temporal duration. Therefore, we use the step segmentation algorithm described below:

We first separate the footprints from the background noise by converting the frame into a binary matrix with a dynamic threshold; by sorting the pixel values of the frame into a 10-bin histogram, the threshold is decided as the center value of the next bin of the highest count bin. Then we put bounding boxes on the binary image by blob detection. Fig. 4 (b) shows all of such bounding boxes added up together based on the raw data from (a), each box is filled with the average pixel value within its region.

To segment a step, we examine the boxes frame by frame until a box's average pixel value is higher than a second dynamic threshold; this threshold is again based on the similar histogram selection method of all the average pixel values of the boxes of all the frames within the captured data of a single walking event. The first positive box passing the threshold is decided as the start of the footstep (a spawning point). Then we track the step in the following frames by looking for the box whose center is closest to the previous box and no more than 30 (pixel distance); when no such box is present, we decide this step has finished.

Since the next step could happen before the finishing of the previous step, the algorithm constantly keeps searching for new spawning points as it tracks existing steps. This algorithm can therefore be compatible with scenarios that multiple people are walking in and out of the same sensor mat.

In our experiment, the step segmentation algorithm for the start and end time results in 97% precision and 91% recall, considering an error margin of ± 2 frames.

B. From Spatio-temporal Domain to Feature Space

After separating the individual steps, we have a sequence of morphing footprints MF of every step as shown in Fig. 5.

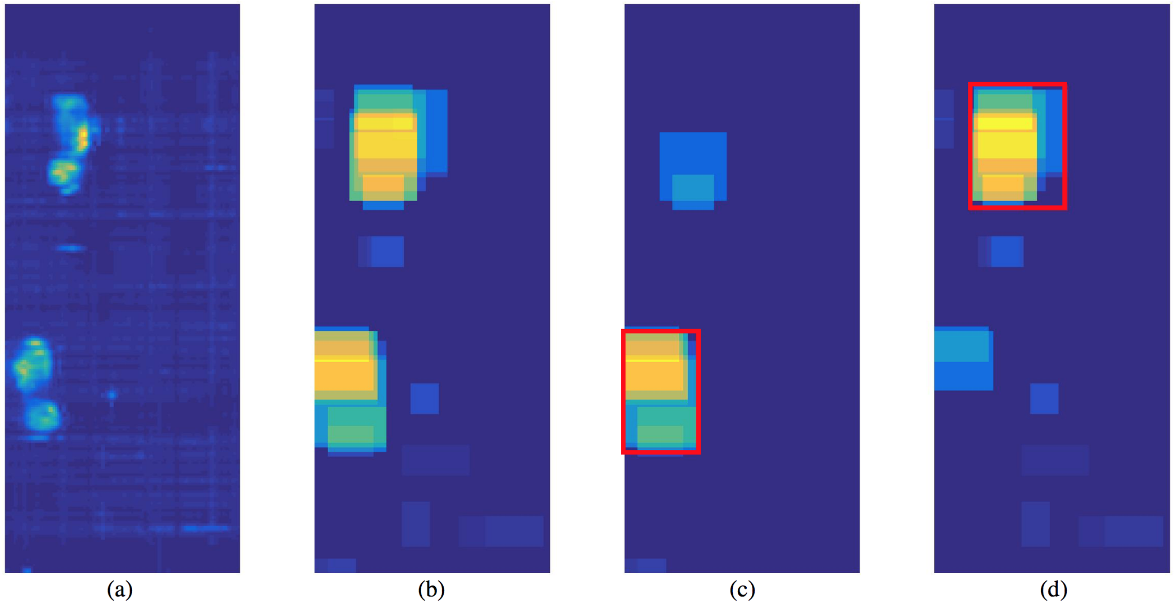

Fig. 4. Step segmentation: (a) sum of pressure mapping over a walking event, (b) all bounding boxes during the event, (c) detection of the first step, (d) detection of the second step

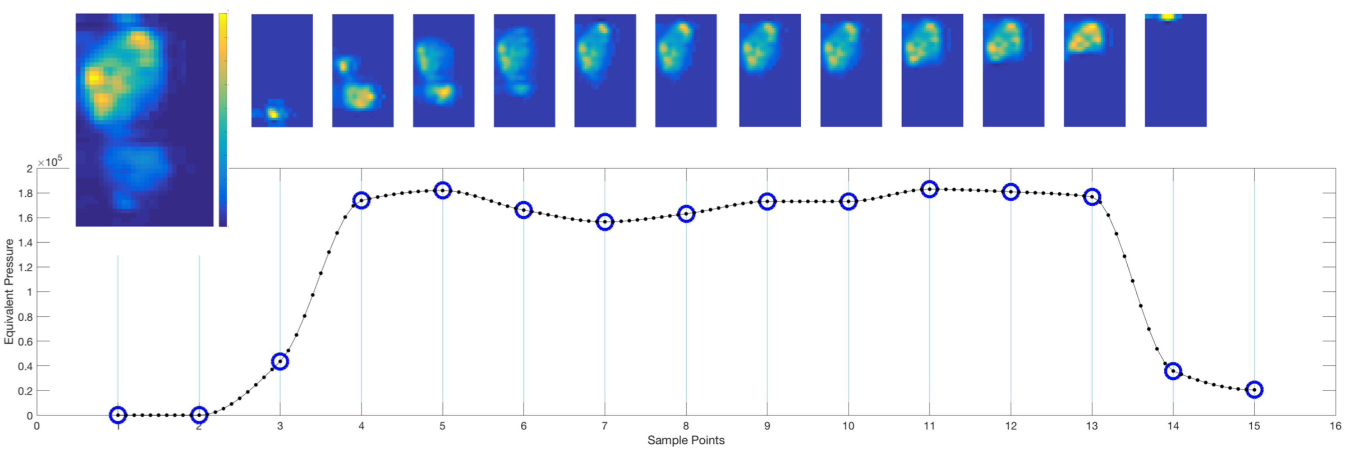

Fig. 5. The morphing footprints of one step (top) and the first attribute - average pixel value (bottom), The blue circles are original data $A_1$and the black dots are A'_1

For every footprint, we calculate the "attributes" $A_i, i \in [1, 7]$ of the footprint profile:

- average pixel value ($i = 1$);
- centroid coordinate ($i = 2, 3$);
- maximum pressure point's value ($i = 4$);
- maximum pressure point's coordinate ($i = 5, 6$);
- pressed area ($i = 7$).

The change of the attributes reflects the change of the shape of the footprint. With a scanning rate of 25Hz, the duration T of every step includes approximately 12 samples, however it changes with the person's walking speed. For a finer temporal analysis we interpolate the sequence of attributes in the time domain to 150 samples as A', this also removes the variation of T caused by the walking speed. In Fig. 5, for example, the blue circles are the average weight attribute calculated from actual samples, and the black dots are interpolated samples. We calculate $mean(A'_i), std(A'_i), var(A'_i), max(A'_i) - min(A'_i)$ for each $i \in [1, 7]$ as the first subset of features.

We apply fast wavelet transform implemented by the LTFAT toolbox [22] to every interpolated attributes A'_i, with 10 filter-bank iterations, 'db8' as the mother wavelet [23], The mean, variance, standard deviation, skewness and kurtosis of the resulting wavelet coefficients of every iteration $C_i, i \in [1, 11]$ are then used as wavelet features $wf(A'_i)$ (for the lower frequencies $i = 1, 2, 3$, only mean values are calculated, limited by the number of coefficients). Therefore, 43 of each attribute A'_i, overall 301 features are derived from wavelet transform as the second subset of features.

On the other hand, we calculate the average of MF in the time domain and result in a static footprint of the step as shown at the left of Fig. 5. We calculate the aforementioned set of 7 attributes of this single frame as the third subset of features Overall, 336 features are calculated. Compared to the work by investigating high definition barefoot footprint [14] and other works with comparing the shapes of footprint, the features we use are much less related to the details to the shape of the foot.

C. Cross-validation Results and Discussion

To classify the person's identity, we use a support vector machine classifier with a quadratic kernel. We carry out 10 fold cross validation and repeated the process with 10 iterations. The average of confusion matrix is shown in Fig. 6 (cell numbers are true positive rates at the diagonal and false negative rates at the rest). From the confusion matrix, certain participants have higher precision and recall rates such as P6, P8 and P9; while P5 has a relatively lower precision, mainly confused with P4 and P10, the recall is still high. Referring to the participants demographic variation (Fig. 2): for example, our tallest and the shortest participants are P13 and P3, both lying in the above-average; yet P4 and P5 have similar weight, BMI and shoe size, and are of the same gender. However, the demographic link requires further experiment with larger participant pool.

The F1-score is calculated as the harmonic mean of the average precision and recall of all 13 people. The average F1 score and accuracy of 77% are well above random (chance level 7.7%). The accuracy increases as we scale down the participant pool by repeated random selection; with 10 participants the average accuracy is 80.1% and 5 participants 86.85%.

In the paper of Yun [15], Table 11 compares the performance of many floor-based systems. We visualize their comparison table together with our own results in Fig. 7, from which it can be seen that our results lie in the average of the previous works. However, it is worth mentioning that many studies use distinct methods as mentioned in Section I-B, most of them consider features from consecutive steps; the ones that consider only single footsteps has the participant-accuracy combination of 11-70.2% [16], 11-79.2% [24], 9-64.2% [25] and 10-63.3% [26].

IV. Conclusion and Future Work

In this paper, we have proposed a person detection system that operates on only individual steps without considering the shape details or inter-step relationships of the footprints. From a pilot evaluation of 13 participants, we have achieved average accuracy of 76.9%. Thanks to the thin and flexible fabric sensor, the floor mat can be rolled up for storage, and easily installed under normal carpets without permanent modifications. We assume this as an advantage for integration into smart living spaces with aesthetic requirements.

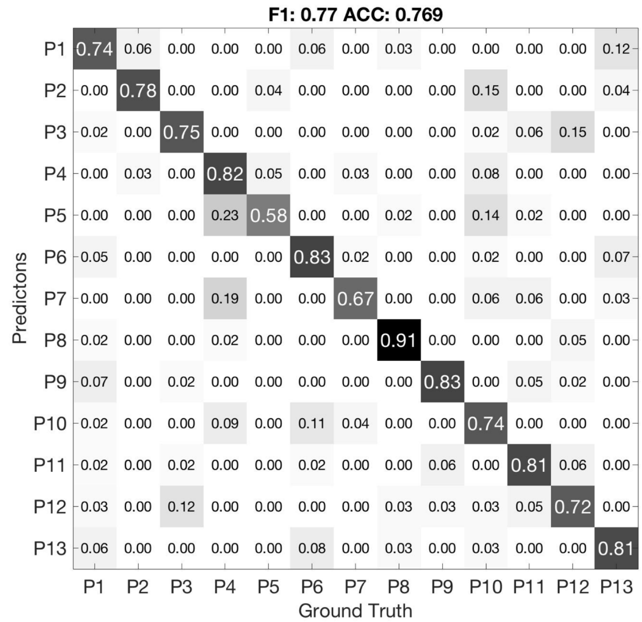

Fig. 6. Confusion matrix of 13 participants, numbers shown are the true positive and false negative rates.

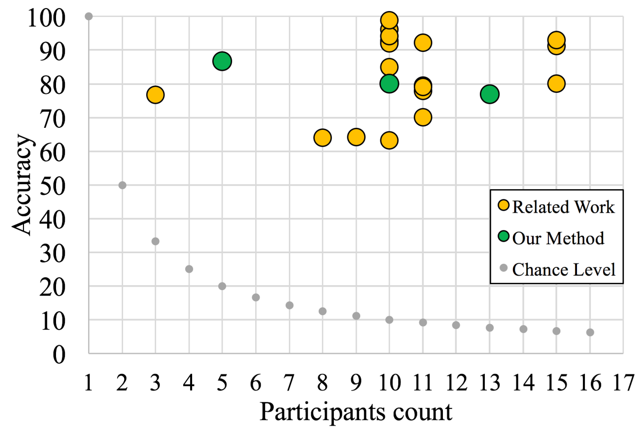

Fig. 7. Performance space visualization of the related work and our approach.

The fabric sensor enables a versatile range of applications. For example, our floor mat can be used as entrance logging at smart homes or smart offices; the identity information can be further utilized by other quarters of the smart living spaces for user-aware automation or interactions. Since we are not considering inter-step features, the system can be scaled up with discrete elements instead of a continuous area. With the result of our previous study in activity recognitions with the pressure sensing fabric, the pressure mat can also be doubled as an ambient activity input ranging from gestures, daily activites to sport exercises [27]. With the step segmentation algorithm, it can also be used as anonymous crowd counting at smart public spaces such as concerts or museums.

Addressing real life conditions such as random shoes and walking path is an emphasis in our future work. For improving the person identification algorithm alone, we would like to conduct larger scale experiments with participants wearing different shoes along multiple days, as such a setting is still a challenge for planar pressure based gait analysis approaches. We would also improve the system to have finer temporal resolution, better signal quality and larger area. Finally, with a larger system, we will also conduct experiments with participants walking in arbitrary paths and taking turns while walking.

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REFERENCES

[1] T. Koskela and K. Väänänen-Vainio-Mattila, "Evolution towards smart home environments: empirical evaluation of three user interfaces," *Personal and Ubiquitous Computing*, vol. 8, no. 3-4, pp. 234–240, 2004.

[2] T. A. Nguyen and M. Aiello, "Energy intelligent buildings based on user activity: A survey," *Energy and buildings*, vol. 56, pp. 244–257, 2013.

[3] R. Y. M. Li, "The usage of automation system in smart home to provide a sustainable indoor environment: a content analysis in web 1.0," *Li, Rita Yi Man (2013), The Usage of Automation System in Smart Home to Provide a Sustainable Indoor environment: A Content Analysis in Web*, vol. 1, pp. 47–60, 2013.

[4] C. N. Scanaill, S. Carew, P. Barralon, N. Noury, D. Lyons, and G. M. Lyons, "A review of approaches to mobility telemonitoring of the elderly in their living environment," *Annals of Biomedical Engineering*, vol. 34, no. 4, pp. 547–563, 2006.

[5] F. Corno and F. Razzak, "Intelligent energy optimization for user intelligible goals in smart home environments," *IEEE transactions on Smart Grid*, vol. 3, no. 4, pp. 2128–2135, 2012.

[6] B. Zhan, D. N. Monekosso, P. Remagnino, S. A. Velastin, and L.-Q. Xu, "Crowd analysis: a survey," *Machine Vision and Applications*, vol. 19, no. 5-6, pp. 345–357, 2008.

[7] M. Sundholm, J. Cheng, B. Zhou, A. Sethi, and P. Lukowicz, "Smart-mat: Recognizing and counting gym exercises with low-cost resistive pressure sensing matrix," in *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing*. ACM, 2014, pp. 373–382.

[8] R. Brunelli and D. Falavigna, "Person identification using multiple cues," *IEEE transactions on pattern analysis and machine intelligence*, vol. 17, no. 10, pp. 955–966, 1995.

[9] U. Dieckmann, P. Plankensteiner, and T. Wagner, "Sesam: A biometric person identification system using sensor fusion," *Pattern recognition letters*, vol. 18, no. 9, pp. 827–833, 1997.

[10] I. Bouchrika, J. N. Carter, and M. S. Nixon, "Towards automated visual surveillance using gait for identity recognition and tracking across multiple non-intersecting cameras," *Multimedia Tools and Applications*, vol. 75, no. 2, pp. 1201–1221, 2016.

[11] F. Castro, M. Marin-Jimenez, N. Guil, and N. P. de la Blanca, "Automatic learning of gait signatures for people identification," *arXiv preprint arXiv:1603.01006*, 2016.

[12] J. Wang, M. She, S. Nahavandi, and A. Kouzani, "A review of vision-based gait recognition methods for human identification," in *Digital Image Computing: Techniques and Applications (DICTA), 2010 International Conference on*. IEEE, 2010, pp. 320–327.

[13] R. J. Orr and G. D. Abowd, "The smart floor: a mechanism for natural user identification and tracking," in *CHI'00 extended abstracts on Human factors in computing systems*. ACM, 2000, pp. 275–276.

[14] T. C. Pataky, T. Mu, K. Bosch, D. Rosenbaum, and J. Y. Goulermas, "Gait recognition: highly unique dynamic plantar pressure patterns among 104 individuals," *Journal of The Royal Society Interface*, vol. 9, no. 69, pp. 790–800, 2012.

[15] J. Yun, "User identification using gait patterns on ubifloorii," *Sensors*, vol. 11, no. 3, pp. 2611–2639, 2011.

[16] J. Suutala and J. Röning, "Towards the adaptive identification of walkers: automated feature selection of footsteps using distinction-sensitive lvq," in *Int. Workshop on Processing Sensory Information for Proactive Systems (PSIPS 2004)*, 2004, pp. 14–15.

[17] K. Nakajima, Y. Mizukami, K. Tanaka, and T. Tamura, "Footprint-based personal recognition," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 11, pp. 1534–1537, 2000.

[18] G. Qian, J. Zhang, and A. Kidané, "People identification using gait via floor pressure sensing and analysis," in *European Conference on Smart Sensing and Context*. Springer, 2008, pp. 83–98.

[19] M. Sousa, A. Techmer, A. Steinhage, C. Lauterbach, and P. Lukowicz, "Human tracking and identification using a sensitive floor and wearable accelerometers," in *Pervasive Computing and Communications (PerCom), 2013 IEEE International Conference on*. IEEE, 2013, pp. 166–171.

[20] "Sefar ag." [Online]. Available: http://www.sefar.com/

[21] B. Zhou, J. Cheng, M. Sundholm, and P. Lukowicz, "From smart clothing to smart table cloth: Design and implementation of a large scale, textile pressure matrix sensor," in *ARCS2014*. Springer LNCS, 2014.

[22] Z. Průša, P. L. Søndergaard, N. Holighaus, C. Wiesmeyr, and P. Balazs, "The large time-frequency analysis toolbox 2.0," pp. 419–442, 2014.

[23] I. Daubechies, "Ten lectures on wavelets," 1992.

[24] J. Suutala and J. Roning, "Combining classifiers with different footstep feature sets and multiple samples for person identification," in *Proceedings.(ICASSP'05). IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005.*, vol. 5. IEEE, 2005, pp. v–357.

[25] J. Suutala, K. Fujinami, and J. Röning, "Gaussian process person identifier based on simple floor sensors," in *European Conference on Smart Sensing and Context*. Springer, 2008, pp. 55–68.

[26] J. Suutala and J. Röning, "Methods for person identification on a pressure-sensitive floor: Experiments with multiple classifiers and reject option," *Information Fusion*, vol. 9, no. 1, pp. 21–40, 2008.

[27] J. Cheng, M. Sundholm, B. Zhou, M. Hirsch, and P. Lukowicz, "Smart-surface: Large scale textile pressure sensors arrays for activity recognition," *Pervasive and Mobile Computing*, 2016.