User Identification Using User's Walking Pattern over the ubiFloorII

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Abstract. In this paper, we propose ubiFloorII, a novel floor-based user identification system to recognize humans based on their walking pattern such as stride length, dynamic range, foot angle, and stance and swing time. To obtain users walking pattern from their gait, we deployed photo interrupter sensors instead of switch sensors used in ubiFloorI. We developed a software module to extract walking pattern from users' gait. For user identification, we employed neural network trained with users' walking samples. We achieved about 96% recognition accuracy using this floor-based approach. The ubiFloorII system may be used to automatically and transparently identify users in home-like environments.

1 Introduction

With the availability of diverse sensors and computing power, it is becoming possible to provide the users with personal location-based services. For providing convenient services to users, reliable person identification through automatic, transparent, and often remote means is a must. Surrogate representations of identity such as password have been successful in conventional computers. However, in ubiquitous computing environments where computing resources exist everywhere, it is necessary to perform user identification through various means.

One approach in user identification is RFID (Radio Frequency IDentification) system [1, 2, 3]. RFID system has the potential to accurately recognize humans and is robust against environmental factors around an individual like light intensity. A disadvantage of RFID system is that individuals must always carry or attach sensors to their body, and may lose it.

Biometrics, which refers to automatic recognition of people based on their distinctive anatomical (e.g., face, fingerprint, iris, retina, hand geometry) and behavioral (e.g., signature, gait) characteristics, can provide automatic, secure, and user-friendly person identification solutions. This is because biometric identifiers cannot be shared or misplaced, and they intrinsically represent the individual's bodily identity [6]. However, the currently available biometrics systems have not yet carried out automatic and transparent human recognition because of several limitations [4, 5]. For example, the accuracy of camera-based systems is susceptible to the environmental factors like obstacles, shadow, and light intensity.

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Gait recognition means to recognize an individual based on distinctive personal characteristics in gait which refers to the individual's style of walking. Much evidence to support the utility of gait in recognizing people has been reported in other domains such as biomechanics, mathematics, and psychology which suggest that gait is unique [7]. Gait recognition systems can be divided into two categories: (i) vision-based [7, 8] and (ii) floor-based approach [9, 10]. Although vision-based approach has many advantages, extracted features are sensitive to environmental factors and individual's privacy can be compromised because of camera surveillance. On the contrary, floor-based approach preserves privacy and is available without regard to light. Examples of this approach include active floor [9] and smart floor [10]. These floors consist of load cells and tiles. Features are extracted from the vertical GRF (Ground Reaction Force) signals derived from the individual's footsteps. Experimental results showed respectively 91% and 93% correct footstep identification with 15 subjects. However, these systems need expensive load cells to get user's stepping pattern (i.e., GRF signal). To track a resident, living room should be equipped with a large number of tiles. Thus, cost of the recognition system would be high.

To overcome the shortcomings of previous systems, we proposed the ubiFloorI, peculiar carpet where 144 switch sensors are uniformly arranged [11]. We extracted walking pattern including stride length, dynamic range, and foot angle from switch sensors, and used neural network to identify unknown walking samples. The experiments showed 90% recognition with 10 subjects. An advantage of the ubiFloorI is that it adopts inexpensive switch sensors instead of load cells, thus cost of system is reduced. This is because walking pattern is used instead of stepping pattern. Nevertheless, we could not use time information like stance and swing time, and stepping pattern like transitional footprint because of low resolution of the floor. Moreover, the centralized architecture of data acquisition was unfavorable for maintenance and extension of the system.

In this paper, we propose the ubiFloorII, a new floor-based user identification system to recognize humans based on their stepping pattern as well as walking pattern. To narrow the scope of the paper, we leave out the detailed organization

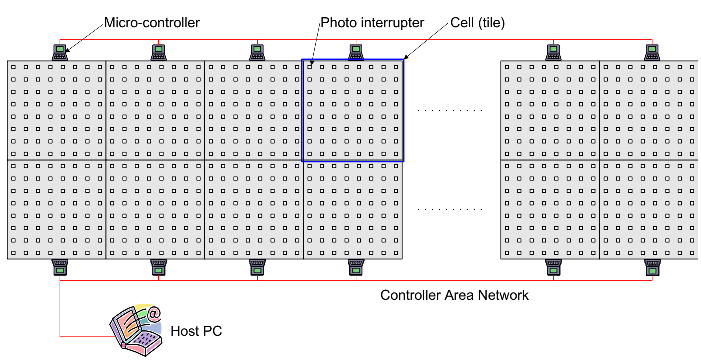

Fig. 1. Overall structure of the ubiFloorII system

Fig. 2. Implemented ubiFloorII

of the ubiFloorII system [12]. Fig. 1 shows overall structure of the ubiFloorII system. The ubiFloorII consists of a 12×2 array of wooden tiles. Each wooden tile measures 30cm square and 64 photo interrupter sensors are uniformly arranged in each tile. A micro-controller is responsible for data acquisition from a corresponding tile and transmits obtained information to the host PC through CAN (Controller Area Network) cable. Then, the host PC extracts user's walking features from received data and recognizes the user with well-trained neural network. Fig. 2 shows our implemented ubiFloorII system.

2 User Identification with the ubiFloorII

2.1 Walking Pattern Extraction

The software modules we have developed for extracting walking pattern from data sets fall into two categories: (i) step-feature extraction and (ii) walking-feature extraction.

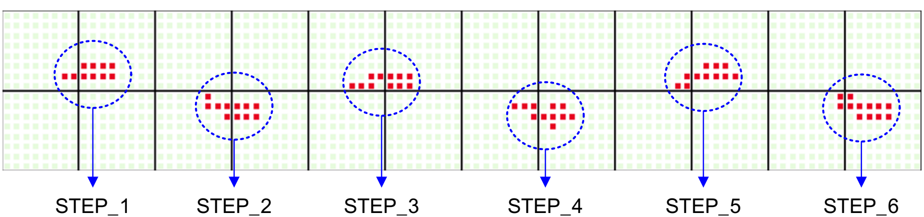

Fig. 3. An example of searching footprints

The step-feature extracting software is used to search all footprints in the data sets received during one walking over the ubiFloorII as shown in Fig. 3. We created the 8×4 footprint model to cover all probable footprints and chose three step-features as follows.

- The X index of the backmost sensor in a footprint
- The Y index of the backmost sensor in a footprint
- The footprint model of a footstep

Fig. 4 displays the footprint model extracted from the STEP_1 footprint in Fig. 3. As shown in Fig. 4, the backmost sensor in a footprint becomes the seed sensor and the other features can be extracted based on the seed sensor. We

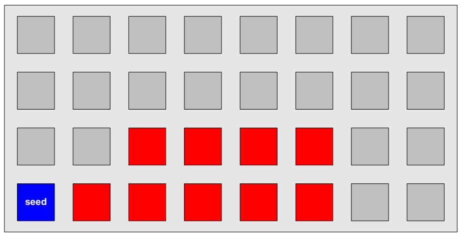

Fig. 4. An example of footprint model

extracted walking-features using the feature values obtained from step-feature extraction as inputs of walking-feature extracting software. We adopted seven walking-features as follows.

- FX: physical X coordinate of the backmost sensor in a footprint
- FY: physical Y coordinate of the backmost sensor in a footprint
- com_FX: compensated X coordinate based on footprint model
- com_FY: compensated Y coordinate based on footprint model
- $nSensor$: the number of pressed sensors in a footprint
- $fStart$: heel-strike time of a footstep
- $fEnd$: toe-off time of a footstep

FX and FY represent the physical X and Y coordinates of the seed sensor in a footprint with the bottom-left corner of the ubiFloorII as origin. Coordinates com_FX and com_FY represent the center of a footprint based on footprint model as shown in Fig. 5. Practically, com_FX and com_FY comprehend user's stride length, dynamic range, and foot angle. $fStart$ and $fEnd$ imply user's stance and swing time in walking. Finally, to create input vectors to our neural network, we need to make the sequences of each walking-feature in terms of footsteps such as $[com\_FX1, com\_FX2, com\_FX3, \ldots]$.

2.2 User Identification

We used multilayer perceptron networks for identifying individuals based on extracted walking features. Our neural network consists of three layers as shown in Fig. 6: (i) input layer N_1 with P_1 neurons, (ii) hidden layer N_2 with P_2 neurons, and (iii) output layer N_3 with P_3 neurons. The input layer N_1 represents the

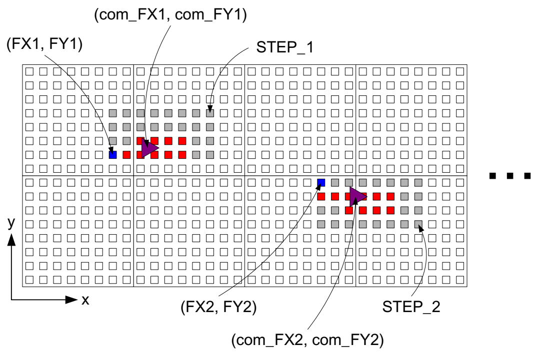

Fig. 5. Walking feature extraction

individuals' walking features space. In the output layer N_3, we can choose the index number of the output node with maximum output values as the user's identification number.

$$User\_Number = max(O_1, O_2, ..., O_M) \quad (1)$$

where O_i denotes the output values of ith node, and M is the number of users. For our neural networks, the transfer function for the hidden layer is tangent-sigmoid and the transfer function for the output layer is pure-linear.

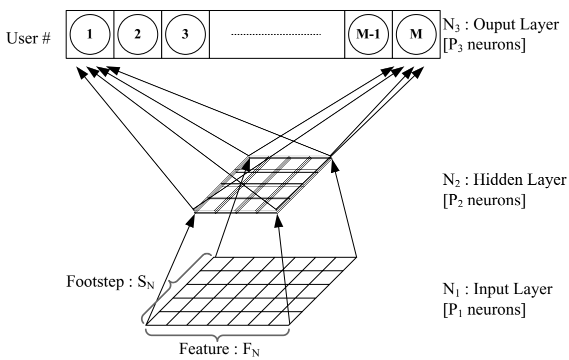

Fig. 6. Structure of neural network for user identification

3 Experiments

3.1 Experimental Population and Conditions

We had the following related hypotheses for walking samples we gathered.

– The subjects maintain walking pattern as regularly as possible.

– The target of our proposed system is home where the size of family is smaller than 10.
– While walking, the subjects listen to smooth music so that the variations of walking pattern are practically reduced.

We gathered walking samples for 10 subjects. They were aged between 27 and 35, and were 165 to 180cm tall. For each subject, we gathered 50 walking samples with the ubiFloorII. In total, we collected 500 walking samples. Depending on users' stride length, it took them five or six footsteps to cross the ubiFloorII. Therefore, we only considered first five footsteps (STEP_1 - STEP_5).

3.2 Walking Feature Sets

To verify the dominant walking features we used five feature sets as inputs to the network. Table 1 shows the combinations of features. In Case 1, coordinates FX and FY are the inputs to the network. This case is used as the standard for evaluating the results with the other feature sets.

Table 1. Classification of feature sets

Case	Features sets	# of inputs
1	FX, FY	10
2	com_FX, com_FY	10
3	com_FX, com_FY, and $nSensor$	15
4	com_FX, com_FY, $fStart$, and $fEnd$	20
5	com_FX, com_FY, $fStart$, $fEnd$, and $nSensor$	25

3.3 Results

We first demonstrate how the number of hidden nodes influences the performance of the neural network. In an effort to decide the optimal number of hidden nodes, we ran an experiment whereby we increased the number of hidden nodes while keeping other parameters fixed, and observed the resulting recognition accuracy. An experimental result with com_FX, com_FY, $fStart$, and $fEnd$ features are shown on the left side in Fig. 7. It shows that about 40 hidden nodes are enough for about 95% recognition rate. We also had experiments to decide *epoch* and *goal*. The right side in Fig. 7 shows that after 1800 epoch, Mean Square Error is smaller than 10^{-4} and this value will be set to the goal.

We present the results of test with our feature sets and a comparative analysis in Table 2. In this experiment, the recognition accuracies were obtained by averaging 10 simulation results while changing the seed value. The seed value determines the initial values of weights and biases of the network. First, we can note that the compensation procedure for com_FX and com_FY results in about 10% improvement in recognition accuracy. Considering Case 2 and 3, Case 3 is worse than Case 2 (i.e., without $nSensor$) because $nSensor$ information already

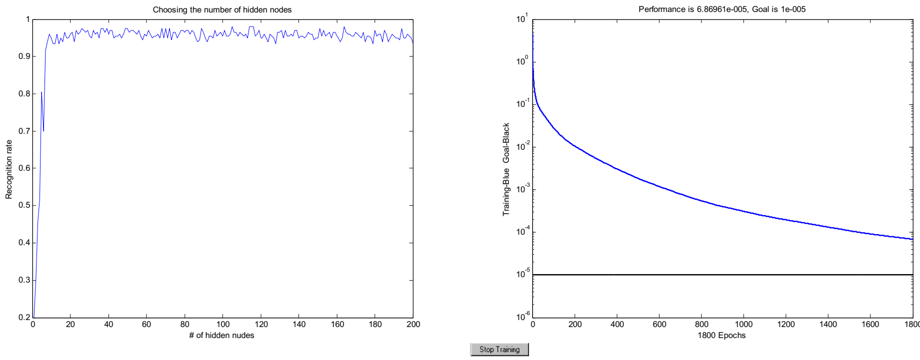

Fig. 7. Results for deciding the number of hidden nodes, epoch, and goal

influenced the compensation procedure for com_FX and com_FY. This result is very similar to that in ubiFloorI. We were able to achieve about 96% recognition accuracy when com_FX, com_FY, $fStart$, and $fEnd$ features were used. Therefore, we can note that stance and swing time is also dominant feature for user identification.

Table 2. Comparison of recognition accuracy

Case	Features sets	Recog. rate(%)
1	FX, FY	80.75
2	com_FX, com_FY	89.05
3	com_FX, com_FY, and $nSensor$	86.85
4	com_FX, com_FY, $fStart$, and $fEnd$	96.20
5	com_FX, com_FY, $fStart$, $fEnd$, and $nSensor$	95.20

We now compare our proposed method with previous floor-based approaches in terms of the recognition accuracy and system architecture. All the floor-based identification systems have about same recognition accuracy. Especially, if user identification would be performed using the stepping pattern as well as walking pattern, the performance of recognition could be definitely improved. Considering system architecture, modularized architecture of the ubiFloorII makes the floor favorable for extension and maintenance. Consequently, our proposed identification method has very wide applications in home-like environments.

4 Conclusion and Future works

In this paper, we have presented a floor-based approach to identify people by their walking pattern. We have designed the ubiFloorII system to provide a way to automatically and transparently recognize users. In the ubiFloorII system, photo interrupter sensors are used to measure the users' walking pattern instead of switch sensors in ubiFloorI. Our achievable accuracy of about 96%, although not wholly successful, is nonetheless enough for common applications in home-like environments. We are further investigating appropriate ways to improve recognition accuracy by combining stepping pattern such as the array of transitional footprints from heel-strike to toe-off.

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