FOOTPRINT TRACKING AND RECOGNITION USING A PRESSURE SENSING FLOOR

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ABSTRACT

This paper presents an approach to clustering, tracking and recognizing footprints of a single subject from pressure data obtained using a pressure sensing floor. The proposed method clusters active footprint areas on the floor and recognizes and tracks the footprints according to their 2D shapes and geometrical relationships among foot clusters. Experimental results show the efficacy of the proposed approach.

Index Terms**—** Pressure sensing floor, footprint tracking

1. INTRODUCTION

Footprint analysis has important applications in biometrics [2, 3, 6] and clinics [4, 5, 7]. Recognizing and tracking footprints is a critical step in these applications based on footprint analysis. Features separately extracted from individual footprint provide a fine-grained picture of the pressure and shape, leading to improved footprint analysis. Existing work on footprint tracking and recognition is limited. To our knowledge, the only published method for footprint tracking from pressure data was proposed in [4], which is a fairly constrained method due to the required prior knowledge about walking direction. In this paper, we describe a method for real-time recognizing and tracking footprints of a single subject performing trained gestures by using the shape and pressure of footprints.

The pressure sensing floor used in our study consists of 96 networked pressure sensing units arranged in a rectangular matrix of 12 rows × 8 columns spanning a total sensing area of 221 (17×13) square feet. Each unit has a pressure sensing mat and associated supporting floor hardware. Each mat is in the size of 19” × 17” with a 48×42 array of 2016 force sensing resistor (FSR) based sensors, resulting in a sensor resolution of 6.25 sensels/in^2. Pressure at each sensor is represented by 8 bits. This system works at up to 44 Hz with average latency of 25 milliseconds. Details about this floor sensing system can be found in [1]. A complete pressure data frame at one time is essentially a 504 × 384 gray scale image. In our research, the proposed footprint tracking and recognition method is implemented on such pressure data acquired by the pressure sensing floor.

2. THE PROPOSED METHOD

The pressure data during a movement is effectively represented by a gray scale image. In our approach, we use the mean-shift algorithm [8] to initially cluster floor pressure data points.

3.1. Mean-Shift Clustering

Mean shift is the process of repetitively shifting data point x to a neighboring local mode of the underlying probability density distribution. Using kernel $G(\cdot)$ centered at time t, the mean-shift vector can be found as

$$M_h(x) \equiv \frac{\sum_{i=1}^{n} G(\frac{x_i - x}{h}) w(x_i)(x_i - x)}{\sum_{i=1}^{n} G(\frac{x_i - x}{h}) w(x_i)} \qquad (1)$$

where $w(x)$ is the sample weight and h is the window size [8]. The shifted data point is $x+M_h(x)$. In our experiment, data points are clustered through the blurring process [8] using the observed pressure data as the weight used in (1). Once the process has converged, the data set will be tightly packed into clusters, with all of the data points located closely to the center of that cluster. (The process is said to the converged either after the maximum number of iterations defined by the algorithm or earlier when the mean shift of centers becomes less than the convergence threshold) After convergence, each cluster has a ‘center’ with an ID number and every data point has a ‘label’ associated with corresponding cluster.

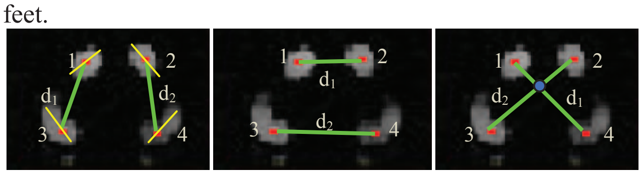
3.2. Footprint Segmentation and Recognition

The problem we need to solve is that given a pair of footprints, how to identify the left and right feet as well as their corresponding ball and heel pressure clusters. This problem is tackled in our research as follows. According the locations of their centers, the four cluster centers from mean-shift are split into two groups, one for each foot. Then, within each group the two clusters are recognized as the ball and the heel clusters and the corresponding foot vector can be found. Finally, according to the directions of the two foot vectors, the left and right feet can be identified since we assume that the two feet are on their corresponding sides of the body. In the following, we will present more details on grouping clusters and determining ball and heel clusters in a cluster group.

Given four clusters, there are six different ways to pair them up so that one pair of clusters will correspond to a foot. For each grouping candidate, we define d_1 and d_2 to be the foot vectors connecting the two clusters in the two groups, as shown in Figure 1. In our approach, a grouping candidate is considered valid if both of the following heuristic conditions hold true.

- G-I: The length of d_1 and d_2 must be approximately equal to each other.
- G-II: The intersection of d_1 and d_2 must be outside of the convex formed by the four cluster centers. This is because the two feet cannot overlap with each other.

G-I and G-II are used to reject invalid groupings as shown in Figures 1 (b) and (c), respectively. Figure 1 (a) shows a valid grouping that correctly pairs up the clusters into two feet.



(a) (b) (c)

Figure 1: Different possible groupings of clusters.

Once the four clusters are grouped into two pairs, one for each foot, the next step is to identify the ball and heel clusters in each group for the corresponding foot. For each cluster, a principal axis can be found by applying the principal component analysis (PCA) on the locations of the points in this cluster. An observation we made use of is shown in Figure 1 (a): when a person is standing on the ground with balanced pressure distribution on both feet, a foot vector (e.g. d_1) is approximately orthogonal to the principal axis of the corresponding ball cluster (e.g. cluster #2), and at the same time, approximately parallel to the principal axis of the corresponding heel cluster (e.g. cluster #1). Hence a ball cluster is labeled if its principal axis is close to orthogonal to the related foot vector. In this way, the ball and heel clusters can be found in both groups. Due to the observation noise and change of foot pressure, sometimes, not all the ball and heel clusters can be identified using this method. In our experiments, we require the subject to start each gesture movement from a standard pose (stand upright with two feet separated) so that in most cases all clusters can be found.

3.2. Footprint Tracking

Once a pressure cluster is correctly assigned with a foot label, mean-shift is able to track the COP of this cluster and to maintain its foot label while the cluster remains on pressure sensing floor.

Tracking individual foot COP can become complicated for gestures that involve foot lifting and stepping. Tricky scenarios can arise. For example, starting from a standing pose with all the clusters correctly labeled, the subject first lifted his left foot and stepped only on its heel and then lifted the right foot and stepped on its ball. In this foot action, there were two new clusters formed through stepping on the left and right feet. On the other hand, there are foot actions that can also create two new clusters. For example, in the previous action, instead of stepping on the lifted right foot, the subject can press on the left ball to create two new pressure clusters. To correctly label these clusters in different cases is challenging.

In the following, we introduce a robust footprint tracking algorithm that maintains the foot identify and groups pressure clusters of the same foot by making use of prior knowledge such as foot length, foot vectors and plausible geometric relationships among the foot clusters existing in the gesture set. To obtain foot vectors for persistent footprint tracking, the grouped pressure clusters are further recognized to be either the ball or the heel of the corresponding foot.

3.2.1. Assumptions

To make the problem more tractable, we assume that the subject is going through a set of gestures (e.g. those shown in Figure 3) with the following held true.

- T-I: Throughout a gesture, there is always a foot on the floor.
- T-II: When a foot is on the floor, the direction of the foot vector stays constant and there is not sliding foot movement on the floor.

3.2.2. Different Types of Pressure Clusters

After processing one frame of pressure data using our footprint tracking algorithm, clusters obtained from mean-shifting fall into three categories: a) the fully-recognized-cluster (FRC) that is assigned with both the foot label (left/right) and part label (ball/heel), b) the partly-classified-cluster (PCC) that is a part (ball or heel) cluster assigned only the foot label but not the part label, and c) the foot-labeled-cluster (FLC) that is known to be a non-part cluster and assigned with only the foot label.

The locations and pressure values of the FRCs, PCCs and FLCs are used to find the COPs of each foot according to their foot labels. At any time instant, there can be at most four FACs, two for each foot. In our footprint tracking algorithm, an FRC and a PCC in the same frame are not allowed to be associated with the same foot. Once an FRC is identified, a list of associated parameters is maintained to help recognize other non-FRC clusters. These parameters include the direction of the foot vector related to this FRC, which stays the same when the corresponding foot is stays on the floor according to T-II, and a reference distance between the ball and heel of the relevant foot.

3.2.3. Tracking

Assume that all clusters in the previous frame have been properly classified and their labels assigned. In the current frame, if there are no new clusters identified by mean-shift, the existing clusters will be continually tracked and the foot COP updated accordingly.

In the case when new clusters are obtained from mean-shift, these newly detected clusters (NDC) will be matched to existing FRCs and PCCs to see if a valid footprint can be formed. The connected component analysis (CCA) is applied to the pressure data to identified connected clusters. NDCs will be first assigned the foot labels of the connected FRC or PCC. For an FRC and an NDC to form a valid footprint, first their foot labels (if the NDC is assigned a foot label based on the results of CCA) must be the same, and then their distance and resulting hypothesis foot vector have to be close to the ones stored in the FRC's parameter list. If an NDC is successfully matched to an FRC, this NDC will be upgraded to an FRC, which forms a complete footprint together with the existing FRC.

When an NDC failed to match with an FRC or there is no available FRC in the current frame (e.g., two existing FRCs already form a complete footprint), it will be matched with a PCC to see if a valid footprint can be formed. If the distance between the NDC and the PCC is within the range of valid foot length, they will be further recognized to either the ball or heel cluster of the related foot. In our proposed approach, two methods are used for ball and heel recognition to handle two different cases. The first case is when there is an FRC of the other foot available in the current frame. In this case, the corresponding foot parameters of this FRC, including the foot vector, locations of the associated ball and heel clusters will be used to correctly recognize the unknown clusters. Given two unknown clusters of the same foot, there exist two possible ball and heel configurations. Together with the FRC parameters of the other foot, each configuration leads to a hypothesis for the locations of the four ball and heel clusters of both feet. The question is which of the two hypotheses is valid. To solve this problem, an empirical distribution of the four foot clusters in a foot-centered coordinate system is first learned and used to solve this hypothesis testing problem. Given a hypothesis consisting of four foot cluster locations, as shown in Figure 2 a right-foot centered 2D coordinate system is first established for the current frame by using the right heel location at the origin and the right foot vector as the direction of the x-axis. In the example shown in Figure 2 the FRC is the ball cluster from the right foot. In this example, the heel of the right foot is not on the floor. Its location can be estimated based on the FRC parameters such as the direction of the foot vector and foot length based on the right ball FRC. To represent the geometric relationship between the four clusters, the location of the left heel (x_{lh},y_{lh}) and the direction angle θ of the left foot vector in this frame-wise right-foot centered coordinate are extracted to form feature vector $z=(x_{lh},y_{lh},\cos(\theta),\sin(\theta))$. Using manually labeled training data, a probability density function (PDF) of z is learned using kernel density estimation method [9] implemented in the Statistical Pattern Recognition Toolbox for Matlab [10]. Using the learned PDF $p(z)$, the cluster configuration producing a higher probability will be selected. When there is not FRC existing in the current frame, to assign part labels to the unknown clusters is more challenging. In our approach, we make use the PCA-based cluster identification method introduced in the previous section to label the unknown clusters.

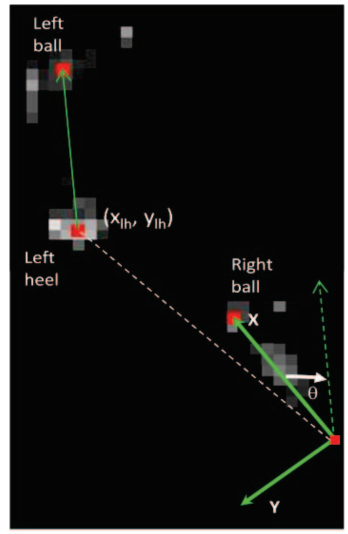


Figure 2: Construction of the frame-wise right-foot centered coordinate system and extracted features for a cluster configuration

4. EXPERIMENTAL RESULTS

To evaluate the proposed method, we collected floor pressure data from two subjects performing seven gestures shown in Figure 3. To learn the PDF $p(z)$ for footprint tracking, 399 frames of pressure data of one subject from five gestures (1, 3, 4, 5, 7) were obtained as training data. The numbers of testing frames of different gestures range from 1901 to 6609. The tracking results are given in Table 1. In this table, N_L is the number of frames in which the tracking algorithm failed to detect the footprints. N_{LR} is the number of frames where the foot labels of the clusters are wrong. N_{BH} is the number of frames where the ball and the heel clusters are switched while the foot labels are correctly assigned. Figure 4 shows tracking results of one of the gestures (Arm-stretching) for frames 988, 1058, 1067, 1074, 1086, 1184, 1226, 1249, 1255 and 1288. In these plots, the color of the marked clusters indicates the foot labels (red for the left foot and green for the right foot) and the shapes such as circle, square and triangle represent ball, heel, and unknown PCC, respectively.

1: Bow-drawing 2: Kicking 3: Side-Bending

Figure 3: Sample images of the seven testing gestures

Table 1 Tracking Errors

Gesture	# of Frames	N_L	N_{LR}	N_{BH}
1	6609	1	30	132
2	3894	0	172	134
3	1901	0	0	0
4	3338	0	0	0
5	5600	0	200	97
6	2797	63	314	178
7	5060	0	9	15

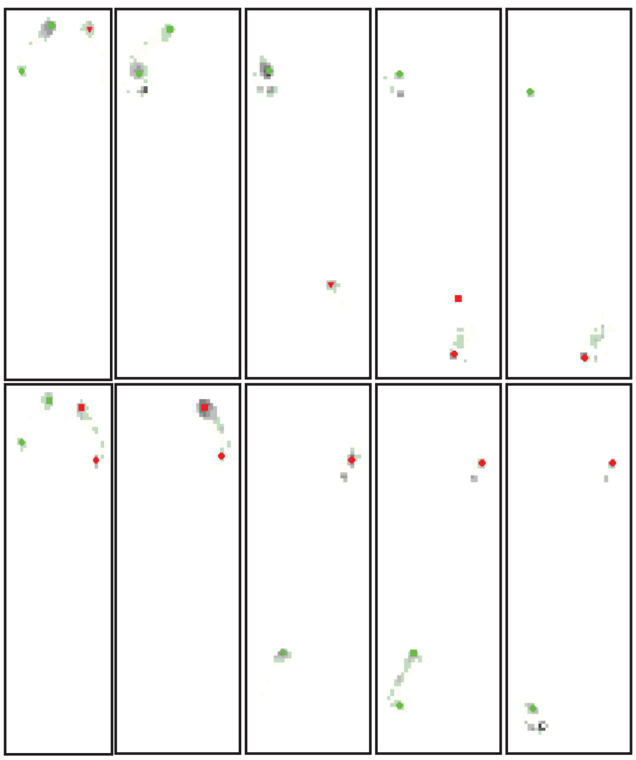


Figure 4: Tracking results of the Arm-Stretching gesture. Different color and shapes of the marks indicate the foot and part label of different clusters. Details can be found in the text.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we have shown that by using simple mean-shifting clustering and spatial and geometrical constraints the footprints of a single subject performing simple gestures can be reliably detected, recognized and tracked. In our future work, we will closely examine the proposed methods using data collected from general movement. In addition, we will investigate the use of 2D shape descriptors for cluster recognition to improve the tracking accuracy.

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