Bayesian Analysis of Sub-Plantar Ground Reaction Force with BSN

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Abstract— **The assessment of Ground Reaction Forces (GRF) is important for gait analysis for sports, pathological gaits and rehabilitation. To capture GRF, force plates and foot pressure insoles are commonly used. Due to cost and portability issues, such systems are mostly limited to lab-based studies. Long-term, continuous and pervasive measurement of GRF is not feasible. This paper presents a novel concept of using an ear-worn sensor for pervasive gait analysis. By emulating the human vestibular system, the bio-inspired design sensor effectively captures the shock wave generated by the GRF. A hierarchical Bayesian network is developed to estimate the plantar force distribution from the ear sensor signals. The accuracy of the ear sensor for detecting GRF is demonstrated by comparing the results with a high-accuracy commercial foot pressure insole system.**

Keywords: Bayesian Network, Ground Reaction Force, Gait Analysis, Biomechanics

I. INTRODUCTION

Gait analysis is an important part of orthopedics [1, 2] rehabilitation [3], sport medicine [4, 5] and biomechanics [6, 7]. To quantify gait, motion capture systems, electromyography (EMG) sensors and force plates (or foot pressure insoles) are commonly used to capture kinematics, muscle contraction, and Ground Reaction Force (GRF). In particular, the GRF has been studied since 1886 [8] and previous studies have shown the significance of the GRF in gait analysis and demonstrated many applications for characterizing normal and pathological gaits [9-13].

To measure GRF, force plates or foot pressure insoles are commonly used [14]. Force plates, which are fixed to the ground, can measure the force between the ground and the planar surface of the foot, whereas the foot pressure insoles measure the pressure between the planar surface of the foot and the sole of the shoes. Both systems are costly, thus limiting their use mainly to dedicated biomechanics laboratories. The measurements performed are also constrained to brief time periods which may or may not represent the normal walking/running conditions.

To enable continuous gait measurements, a number of wearable sensing platforms have been proposed. For instance, Aminian *et al.* proposed a gyroscope and foot switch based ambulatory gait measurement system [15]. Takeda *et al.* introduced a wearable gait analysis system which consists of seven sensing units worn on the abdomen and the lower limbs, and each unit consists of a tri-axial accelerometer and three orthogonal positioned gyroscopes [16]. Bamberg *et al.* proposed a "GaitShoe", where a range of wireless sensors including accelerometer, gyroscope, and force sensitive resistors are integrated to a shoe, and it can captured detailed gait parameters [17]. All these systems involve multiple sensors and some require explicit modification of the shoes, thus limiting their widespread use.

In this paper, a novel concept of an ear-worn sensor is presented for pervasive sensing of GRF patterns. To demonstrate the practical value of the system, healthy volunteers were asked to wear the e-AR sensor together with a pair of high-precision commercially available foot pressure sensing insoles for relative performance evaluation. A hierarchical Bayesian network is developed to estimate the planar force distribution from the recorded e-AR sensor signals.

II. THE E-AR SENSOR

The e-AR (ear-worn Activity Recognition) sensor, as shown in Figure 1, is a bio-inspired sensor designed to emulate the main functions of the human vestibular system. It mainly consists of an 8051 processor with a 2.4 GHz transceiver (Nordic nRF24E1), a 3D accelerometer (Analog Devices ADXL330), a 2MB EEPROM (Atmel AT45DB161), and a 55mAhr Li-Polymer battery. Previous studies have demonstrated the ability of e-AR sensor in capturing posture and daily activities, and its applications in postoperative care and patient monitoring [18-20].

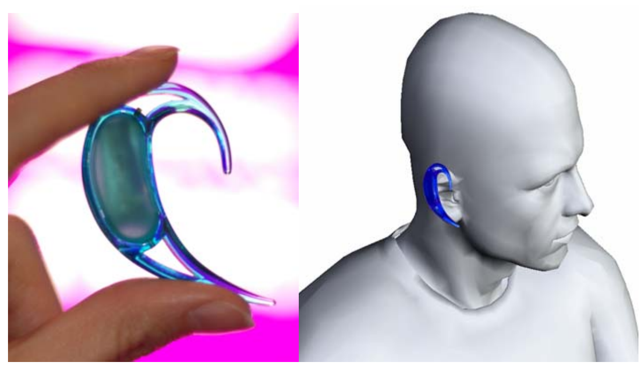

Figure 1. The e-AR sensor used in this study for sensing GRF.

In addition to capturing posture and activities, the e-AR sensor is also sensitive to shock waves generated by GRF. GRFs are the forces exerted by the ground in reaction to the forces that body exerts on the ground through the foot. Whenever the heel strikes, a shock wave is generated and propagated through the skeleton to the cranium, which may

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be picked up from the superior and posterior auricular regions [21]. Folman *et al.* have shown that the axial skeleton does not dissipate the transients or affect their interference where matching signals were found from the accelerometer mounted on the forehead and the accelerometer attached to the tibial tuberosity [22]. This means the axial skeleton is a good conductor for the transient of both high and low-frequency waves generated by the GRFs.

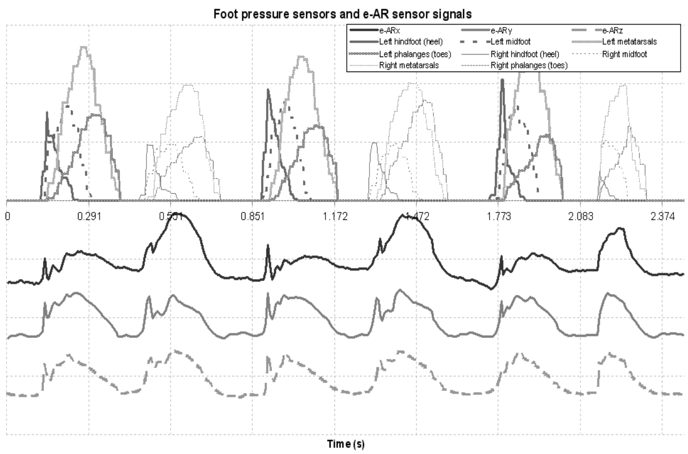

Figure 2. A comparison of the GRF waveforms sensed from the foot pressure sensors and the e-AR sensor.

To illustrate the ability of the e-AR sensor in capturing the GRFs, Figure 2 illustrates the raw signals of the e-AR sensor along with the insole foot pressure sensors worn by a subject running on a treadmill. It is evident that the waveform of the e-AR sensor matches well to that of the pressure sensors. It also accurately captures the timing of the heel strike as highlighted in the graph.

III. PLANTAR FORCE DISTRIBUTION

Among different parameters of the GRF, we have focused on the plantar force distribution in this study to demonstrate the concept of using the e-AR sensor for gait analysis. Previous research has shown the significance of the plantar force distribution in analyzing pathological gaits [12, 13]. In this study, instead of estimating the foot pressures, the instances of ground contact at different regions of the foot are inferred by using the e-AR sensor.

Figure 3 schematically illustrates the sub-plantar regions used for this study. The forefoot is divided into phalanges (toes) (T) and metatarsals (F), whereas M represents the midfoot (the five tarsal bones) and H represents the hindfoot (the talus and the calcaneus or the heel). Each region is further separated into lateral (O) and medial (I) halves. For example, HO means the lateral hindfoot region

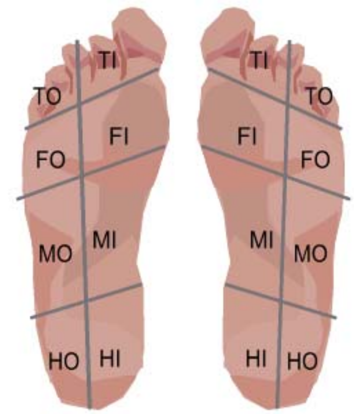

Figure 3. The sub-plantar regions used for GRF analysis.

In this study, a Bayesian Network approach has been chosen to analysis the eAR sensor signals. Bayesian networks have been widely used in pattern recognition and machine learning applications [23-27]. Its graphical and causal structure representation enables visual and statistical modeling of the underlying problem domain. Its abilities in modeling Markov processes have facilitated the interpretation of words and phonemes in speech recognition [28-30] and human behaviors in computer vision [31-33].

A hierarchical Bayesian network is designed to estimate the plantar force distribution. The network is designed to match different phases of the foot strike (i.e. three layers of networks are designed to detect foot step, heel (hindfoot) strike, and lateral hindfoot strike). The parameters of the network are learned from the sensor data (20% of all the sensor data was used for the learning phase). At the bottom layer of the network, a naïve Bayesian is constructed to detect steps where the three orthogonal signals of the e-AR sensor (i.e., e-AR$_x$, e-AR$_y$, e-AR$_z$ correspond to the lateral, vertical and fore-aft accelerations) are represented as the child nodes as shown in Figure 4 (left).

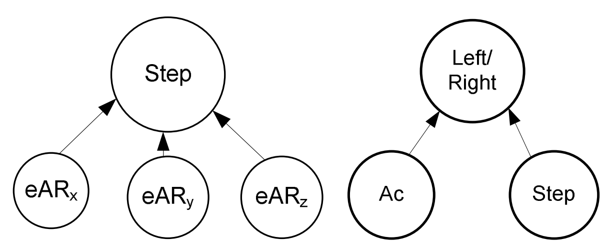

Figure 4. Bayesian networks for detecting steps (left) and left/right foot strikes (right).

Each step is detected by calculating the maximum a-posteriori probability (MAP):

$$\begin{aligned} Step &= \arg\max P(Step \mid eAR_x, eAR_y, eAR_z) \\ &= \arg\max\left[\alpha \prod_{i=x,y,z} P(eAR_i \mid Step) P(Step)\right] \end{aligned} \tag{1}$$

where α is a normalizing constant. As the 3D accelerometer captures the acceleration in three orthogonal directions, conditional independence can be assumed among these sensor signals.

The output of the step detection together with the accumulated signal Ac are then fused to determine whether it is a left or right foot strike as shown in Figure 4 (right). The posterior probability can therefore be calculated as follows:

$$P(LR \mid Ac, Step) = \alpha P(Ac \mid LR) P(Step \mid LR) P(LR) \qquad (2)$$

where variable Ac is the accumulated value of the lateral acceleration (i.e. e-AR$_x$).

$$Ac(t) = \begin{cases} eAR_x(t) + eAR_x(t-1), & eAR_y > 0 \\ 0 \quad , & else \end{cases} \qquad (3)$$

To capture the stance phase of the gait (i.e., from heel strike to toe off), the vertical acceleration signal is fused with the output of the step-detection network to infer the force contact at different areas of the foot. This is depicted in Figure 5.

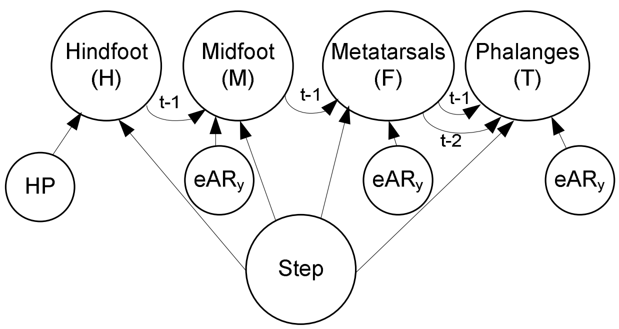

Figure 5. Bayesian networks for capturing the hindfoot, mid-foot, the metatarsals and phalanges contacts.

To detect heel-strike, a high pass filter is used to extract the high frequency shock waves and the posterior probability of the heel (hindfoot) strike is formulated as follows:

$$P(H \mid HP, Step) = \alpha P(HP \mid H) P(Step \mid H) P(H) \qquad (4)$$

where HP is the high pass filtered signal of the vertical acceleration (i.e., e-AR$_y$) signal from the e-AR sensor.

It can be assumed that the stance phase is Markovian, to enhance the inference of the mid-foot detection, the past states of the hindfoot contact is fused with the vertical acceleration and the posterior probability is calculated as follows:

$$P(M \mid H_{t-1}, eAR_y, Step) = \alpha \prod_{k=H_{t-1}, eAR_y, Step} P(k \mid M) P(M) \qquad (5)$$

where H_{t-1} represents the state of the hindfoot detection in the previous time step. Likewise, the posterior probabilities of the metatarsals (F) and phalanges (T) contact detections are formulated as follows:

$$P(F \mid M_{t-1}, eAR_y, Step) = \alpha \prod_{k=M_{t-1}, eAR_y, Step} P(k \mid F) P(F) \qquad (6)$$

$$P(T \mid F_{t-1}, F_{t-2}, eAR_y, Step) = \alpha \prod_{k=F_{t-1}, F_{t-2}, eAR_y, Step} P(k \mid T) P(T) \qquad (7)$$

The medial (I) and lateral (O) foot contacts are then inferred by fusing the lateral acceleration with the step detection, and the corresponding Bayesian network is depicted in Figure 6.

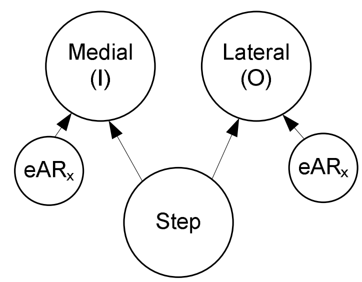

Figure 6. Bayesian Networks for capturing medial and lateral foot contacts.

Accordingly, the posterior probabilities are calculated as follows:

$$P(I \mid eAR_x, Step) = \alpha P(eAR_x \mid I) P(Step \mid I) P(I) \qquad (8)$$

$$P(O \mid eAR_x, Step) = \alpha P(eAR_x \mid O) P(Step \mid O) P(O) \qquad (9)$$

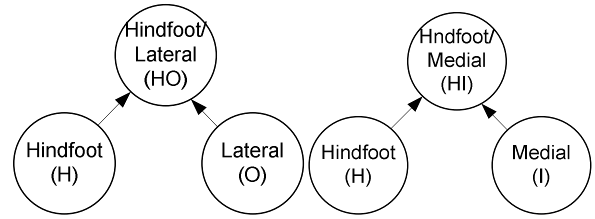

Figure 7. Bayesian networks for capturing the contacts at the subdivided regions HO (left) and HI (right).

The detection in the subdivided regions, such as HO, is inferred by fusing the results from the corresponding regions, such as H and O. Figure 7 depicts the Bayesian networks for detecting the HO and HI contacts, and the posterior probabilities for the subdivided regions are formulated as follows:

$$P(\psi \mid \xi, \varsigma) = \alpha \prod_{k=\xi,\varsigma} P(k \mid \psi) P(\psi) \quad (10)$$

where

$$\psi = \{HO, HI, MO, MI, FO, FI, TO, TI\}$$
$$\xi = \{H, H, M, M, F, F, T, T\}$$
$$\varsigma = \{O, I, O, I, O, I, O, I\}$$

ψ represents the series of subdivided regions, ξ represents the series of the hindfoot to phalanges regions, and ς represents the series of medial and lateral regions.

IV. EXPERIMENT

To validate the accuracy of the e-AR sensor in capturing the ground reaction forces, a Paromed Parotec insole foot pressure sensor array (Neubeuern, Germany) is used. The experimental setup is shown in Figure 8 and the system consists of two insoles and each insole has 24 pressures sensors. The actual pressure applied on each pressure sensors can be recorded onto a waist mounted recorder.

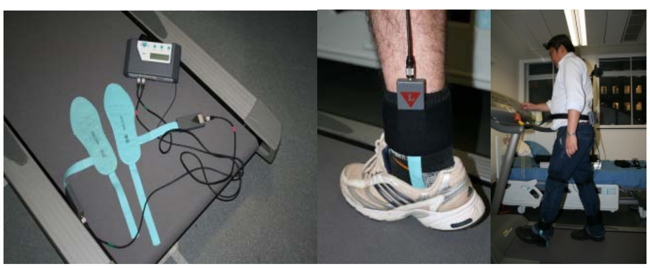

Figure 8. Experimental setup for the use of the Paromed Parotec foot pressure measurement system for collecting reference plantar pressure distributions.

As a proof of concept study, six volunteers were recruited for the study. The subjects were asked to wear the e-AR sensor and the pressure insoles and run on a treadmill with a fixed speed of 10km/hr. Both the e-AR sensor and the foot pressure sensor data were recorded simultaneously when the subject was running on the treadmill. Due to the limited memory on the foot pressure recorder, only a couple of minutes of data can be recorded.

V. RESULTS

Detailed classification results are listed in Table 1. It is evident from the table that the e-AR sensor can detect each step (Step) and identify left or right foot strike (L/R) very accurately. In terms of the proximodistal pressure transitions, (i.e., from H to T), a relatively high accuracy has been achieved with an average sensitivity and specificity of 88% and 83%, respectively. A slightly weaker performance is found in detecting the medial and lateral contact forces and the corresponding average sensitivity and specificity is 88% and 77%, respectively. The detection on the subdivided regions, such as HO and HI, high accuracies are achieved in the hind-foot, mid-foot and the metatarsals regions, but not in the phalanges areas. The overall averaged sensitivity and specificity for the sub-plantar regions are 85% and 84%, respectively.

VI. CONCLUSION

This paper presents a novel concept of using an ear-worn sensor for pervasive sensing of sub-plantar pressure transition for gait analysis. A hierarchical Bayesian network has been developed for inferring the plantar force contacts from the e-AR sensor signals, and the accuracy of the proposed system is assessed by using direct insole pressure measurement (Paromed Parotec insole pressure sensor array). The experiment results have shown that the e-AR sensor can accurately detect GRF transition in sub-plantar regions. Certain temporal gait features, such as hike strike, toe off, and stride frequency, can be derived from the GRF transitions. This permits detailed analysis of gait features in a simple, non-intrusive, and truly pervasive manner.

TABLE I. RELATIVE CLASSIFICATION RESULTS FOR SUB-PLANTAR REGIONS FOR THE SIX SUBJECTS STUDIED.

	Sensitivity	***Specificity***
Step	94.23 ± 1.44	91.18± 6.12
L/R (left/right)	98.05± 3.25	97.88± 4.59
H (hindfoot)	90.29± 4.48	88.70± 6.40
M (midfoot)	95.07± 2.00	86.80± 4.45
F (metatarsals)	88.30± 8.50	81.62± 6.88
T (phalanges)	77.44± 9.94	74.05± 4.10
O (lateral)	81.72±11.04	73.70±11.09
I (medial)	93.71± 3.62	81.69± 5.78
HO	89.60± 6.70	87.46± 6.53
HI	89.43± 6.17	88.69± 6.37
MO	82.95±12.11	89.57± 4.51
MI	93.57± 3.65	84.53± 3.38
FO	89.74± 6.33	87.64± 4.36
FI	83.07± 9.43	81.22± 6.22
TO	72.06±15.49	76.20± 9.37
TI	75.65±10.77	75.12± 4.77

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