Information Fusion 41 (2018) 255–263

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

A fusion framework to estimate plantar ground force distributions and ankle dynamics

Fani Deligianni, Charence Wong, Benny Lo, Guang-Zhong Yang*

Hamlyn Centre, Imperial College London, United Kingdom

ARTICLE INFO

Article history:
Received 26 March 2017
Revised 13 July 2017
Accepted 10 September 2017
Available online 14 September 2017

2010 MSC:
00-01
99-00

Keywords:
Gait analysis
e-AR
Fusion of sensors gait data and video

ABSTRACT

Gait analysis plays an important role in several conditions, including the rehabilitation of patients with orthopaedic problems and the monitoring of neurological conditions, mental health problems and the well-being of elderly subjects. It also constitutes an index of good posture and thus it can be used to prevent injuries in athletes and monitor mental health in typical subjects. Usually, accurate gait analysis is based on the measurement of ankle dynamics and ground reaction forces. Therefore, it requires expensive multi-camera systems and pressure sensors, which cannot be easily employed in a free-living environment. We propose a fusion framework that uses an ear worn activity recognition (e-AR) sensor and a single video camera to estimate foot angle during key gait events. To this end we use canonical correlation analysis with a fused-lasso penalty in a two-steps approach that firstly learns a model of the timing distribution of ground reaction forces based on e-AR signal only and subsequently models the eversion/inversion as well as the dorsiflexion of the ankle based on the combined features of e-AR sensor and the video. The results show that incorporating invariant features of angular ankle information from the video recordings improves the estimation of the foot progression angle, substantially.

© 2017 Published by Elsevier B.V.

1. Introduction

Gait analysis is a well-established method for analysing the biomechanics of gait, and a means to capture effective and quantitative assessments for orthopaedic and neurological rehabilitation. Motion capture with topical tracking systems, force plates, instrumented treadmills and pressure sensing insoles are instruments for measuring the heel, subtalar, ankle and knee joint angles, and analysing the force exerted on the ground for accurate analysis of the biomechanical indices of subjects. Although such instrumentations are widely available, the high cost and long set up times typically required have restricted the use of such instruments in major hospitals for routine measurement of certain patients.

Pathological gait is difficult to describe, since it involves atypical ankle kinematics. Nevertheless, it is characterized by the periodic movement of each leg from one position to the next and the corresponding ground reaction forces that support the motion of the body. The ankle is the lower joint and the first to respond to the impact of the foot with the ground. In particular, the subtalar joint, which is lateral to the ankle, is responsible for most of the inversion and eversion of the foot, which plays a significant role in the toe-off phase of the gait as it provides the propulsion to lift the foot. In other words, ground reaction forces along with ankle eversion/inversion and dorsiflexion play a key role in the biomechanical dynamics. Several recent studies have shown that certain gait characteristics can be related to abnormal posture, the development of osteoarthritis and sports related injuries [1–5]. For example, Kuhman et al. has shown that lower leg and foot dynamics are related to the development of injuries in runners [2]. Furthermore, greater rear-foot pronation has been associated with greater pressure on the medial portions of the plantar surface during walking and it has been observed in individuals with poor postural control [5].

To measure the lower limb kinematics accurately expensive multi-camera configuration systems are used to detect and track reflective skin markers. However, the confined spaces typically available in clinics or at home means these methods cannot easily be applied in these scenarios. The use of monocular vision has also been proposed for a number of gait analysis applications, such as biometric authentication [6], diagnosis of Parkinson's disease [7], and identification of abnormalities for assisted living [8,9]. Some of these works map the 2D extracted trajectories to 3D word coordinate system based on deep neural networks and require several labeled training sets. Furthermore, they assume large distances between the subject and the camera and assumptions that the body mass is planar. This does not allow an accurate estimation of the

* Corresponding author.
E-mail address: g.z.yang@imperial.ac.uk (G.-Z. Yang).
URL: https://www.imperial.ac.uk/hamlyn-centre/ (G.-Z. Yang)

http://dx.doi.org/10.1016/j.inffus.2017.09.008
1566-2535/© 2017 Published by Elsevier B.V.

ankle dynamics and the foot progression angle. Furthermore, estimation of ground reaction forces are also important to determine the health risks over time due to excessive joint loading rates and stress. Accurate measurements of ground reaction forces normally require pressure insoles, which are placed inside the shoes.

Recently, wearable wireless body worn sensors have been proposed for detailed gait analysis [10,11]. Our previous work has shown the feasibility and accuracy of using the ear-worn activity recognition (e-AR) sensor for detailed gait analysis and activity recognition [12,13]. This lightweight and miniaturized sensor, e-AR, enables pervasive and continuous monitoring of user with negligible distraction to their normal daily activities. In previous work, we have demonstrated the feasibility of using the e-AR sensor with a hierarchical Bayesian Network framework for estimation of GRFs for normal gait [14]. This hierarchical model allowed characterisation of the plantar force timing distribution based on e-AR measurements only. In a recent article, Clark et al. showed that it is possible to predict vertical ground reaction forces in runners based on the body mass, the contact time between steps and the swing time only [15]. [16,17] compare the advantages of inertial and vision for gait analysis. Although the wearable sensor can estimate the temporal distribution accurately, other detailed gait parameters, such as subtalar joint angle are more difficult to be determined based on inertial sensors only.

In this paper, we propose a novel integrated approach of using the e-AR sensor together with a single video camera, and introduce a framework to fuse the sensing and visual features to reveal the interaction of ground reaction forces and ankle dynamics during normal and abnormal walking. In particular, we utilize Canonical Correlation Analysis with a fused-lasso penalty (fCCA) to extract features across steps that reveal correlations between the e-AR signal and the timing distribution of key gait events. These events occur when ground reaction forces are maximized in the plantar foot areas, such as heel, mid-foot, front-foot and toes. In a two-steps approach, we use fCCA again to fuse the e-AR signal with features derived from the video analysis of a single camera that reflect an angular interaction between the two legs during walking. In this way, we are able to create a prediction framework of the dorsiflexion and inversion/aversion foot angles during heel, mid-foot, front-foot and toe contacts with the ground.

2. Methods

2.1. Data fusion framework

Both normal and pathological gait exhibit repetitive patterns of motion of the lower limbs. In this paper, we utilize this to construct a fusion framework that samples across steps of e-AR signal and video recordings to extract features that predict well ground reaction forces timing distributions and subsequently foot angles in key gait events. Therefore, the framework has two main components that are constructed independently but they interact to provide detailed gait characteristics. The proposed fusion framework requires time-series derived from e-AR sensor, insole sensors and video features to be segmented into gait steps, independently. This is also important as it alleviate the need for accurate synchronization between different modalities. An overview of the framework is presented in Fig. 1.

We are interested in learning a relationship between the e-AR acceleration data and the plantar force timing distributions across steps. The e-AR measures acceleration in three axes that are aligned to the body: Medial-Lateral (ML) axis, Superior-Inferior (SI) axis and Anterior-Posterior (AP) axes. On the other hand, ground reaction forces can be measured with foot pressure insoles that record the pressure between the planar surface of the foot and the sole of the shoes. In order to estimate the plantar force distributions, we hierarchically subdivide the foot into the Heel, Mid-foot, Front-foot and Toe regions as well as Medial and Lateral regions. This results in eight sub-regions similar to our previous work [14]. The insole data are pre-processed to detect gait steps based on the pressure difference between left and right foot. Subsequently, for each step the timings of the maximums of the sub-plantar force distributions are defined within each region. These timings represent key gait events and they are important in identifying abnormal gait.

Once both insole and e-AR data are segmented into steps, we normalize the e-AR signal at each step with respect to the time axis based on linear interpolation so that all steps are equally sampled. Note that we concatenate horizontally the combined SI and AP signal along with the ML signal. Subsequently, these vectors are concatenated vertically to form a matrix, $\mathbf{X}$, $m \times 2n$, where m is the number of steps and n is the number of time samples. On the other hand, the response data $\mathbf{Y}$ is a $m \times k$ matrix that reflects the timings of the peaks of the plantar force distribution estimated based on the insole data. k is the number of plantar sub-regions defined. fCCA is used to relate the e-AR waveform data for each step with the GRFs timing distributions obtained from insole data. Canonical correlation analysis is a powerful tool of modelling the correlation between multivariate variables. The projection of $\mathbf{X}$ and $\mathbf{Y}$ on the derived canonical vectors result in maximally linearly correlated variables. Thus, it allows bi-direction predictive modelling of the associated variables and it has been used in high-dimensional spaces of multi-view gait recognition and numerous other applications [18–20]. fCCA is a variant of canonical correlation analysis that applies a fused lasso penalty, which penalizes the L_1 norm of both the coefficients and their successive differences. This enforces both sparsity and smoothness, which is important since the fCCA variables are time-series segments and ordered variables [21]. The implementation of fCCA is based on a penalized matrix decomposition framework, which obeys the following criterion [22,23]:

$$\begin{gathered}\text{maximise}_{\mathrm{u,v}}\mathrm{u}^{\mathrm{T}}\mathbf{X}^{\mathrm{T}}\mathbf{Y}\mathrm{v} \\ \text{subject to}: \|u\|^2 \le 1,\ \|v\|^2 \le 1,\ f_1 \le c_1,\ f_2(v) \le c_2\end{gathered} \tag{1}$$

Here, f_1, f_2 are convex penalty functions that both impose a fused lasso penalty:

$$\mathrm{f(w)} = \textstyle\sum_j \|\mathrm{w_j}\| + \sum_j \|\mathrm{w_j} - \mathrm{w_{j-1}}\| \tag{2}$$

Note that with u fixed, the criterion in Eq. (1) is convex in v, and with v fixed, it is convex in u. Therefore, the objective function of this biconvex criterion increases in each step of an iterative algorithm [23]:

$$\begin{aligned} u &\leftarrow \mathrm{argmax}_{\mathrm{u}} u^T\mathbf{X}^T\mathbf{Y}v \ \text{ subject to}: \ \|u\|^2 \le 1,\, f_1(u) \le c_1 \\ v &\leftarrow \mathrm{argmax}_{\mathrm{v}} u^T\mathbf{X}^T\mathbf{Y}v \ \text{ subject to}: \ \|v\|^2 \le 1,\, f_2(v) \le c_2 \end{aligned} \tag{3}$$

Once the fCCA model has been trained it can be used for prediction:

$$\hat{\mathbf{Y}}_{\mathbf{s}} = (u\mathbf{X}_{\mathbf{s}})^{+}\mathbf{D}v^{+} \tag{4}$$

Where, $\mathbf{D}$ is the diagonal matrix with the canonical correlation scores and $+$ denotes the pseudo-inverse.

The second major component of the fusion framework is the incorporation of video features derived from a single camera. This provides us with the ability not only to delineate important timing gait events but also estimate the angles between the foot and leg that reflect dorsiflexion and inversion/aversion in these key gait points independently of the camera view point. To this end fCCA is applied again to find a relationship between the combined data derived from e-AR and video features, $\mathbf{Z}$, and foot angles, $\mathbf{W}$ estimated in key gait events, such as when GRFs are maximized during heel, mid-foot, frontal-foot and toe contacts with the ground. Therefore, $\mathbf{Z}$ is an $m \times 2n$ matrix, where m is the number of steps

Download English Version:

https://daneshyari.com/en/article/4969110

Download Persian Version:

https://daneshyari.com/article/4969110

Daneshyari.com