Mixture Modeling of Gait Patterns from Sensor Data

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ABSTRACT

Sensor data can be used for monitoring, modeling, and recognition of human activities during daily life or in special situations. In assistive environments, modeling of characteristic walking styles have been studied as well as preventing the falls of the elderly. In this paper, we pre-process and analyze a time series collection of sensor recordings which is publicly available. More specifically, we transform the raw pressure sensor data in the insoles of the shoes to yield binary pressure patterns to indicate contact between the shoe and the ground. We model the marginal probability distributions of the resulting 0-1 data with mixture models of multivariate Bernoulli distributions. We interpret the identified mixture model in terms of gait phases.

Categories and Subject Descriptors

H.2.8. [**Database applications**]: Data mining; I.5.1 [**Pattern recognition**]: Models - Statistical

Keywords

Probabilistic models, finite mixture models, activity monitoring, gait analysis, sensor data

1. INTRODUCTION

Sensor data can be used for monitoring, modeling, and recognition of human activities during daily life or in special situations. Solutions have been presented, for instance, for detecting fall events of the elderly before the actual impact [23], modeling and comparing gait patterns of healthy persons and persons with Parkinson's disease [1] in a clinical setting. The work presented in [5, 6] concentrates on detecting abnormalities in the gait patterns. Our general motivation to use sensor data in the activity monitoring context is to understand the normal gait patterns of individuals, based on recorded sensor data.

In this paper, we will make use of a publicly available time series collection containing sensor recordings in a controlled walking experiment [15]. More specifically, we will analyze the gait patterns from the raw sensor data that records the pressure between the bottom of the shoe and the ground. We propose a pre-processing that depends on the data distributions of each shoe sensor, and threshold the raw sensor data values with the threshold values based on percentiles of the data distributions. Data value 0 indicates no contact with the floor, and 1 indicates firm contact, which will result in multi-dimensional 0-1 time-series. There are four sensors in our shoe, and therefore our pressure patterns will be represented as four-dimensional, binary data vectors. The modeling is performed in the probabilistic modeling domain with finite mixture models of multivariate Bernoulli distributions [22]. The estimation is done in the framework of maximum likelihood estimation using the EM algorithm [7, 3].

The rest of the paper is organized as follows. In Section 2, we review previous related work with relevance to the current contribution. In Section 3, we introduce the publicly available measurement data set, which can be used to experiment with sensor recordings in a controlled experiment setting. In Section 4, we describe the pre-processing of the sensor data and the methodology of analyzing the derived binary time series from the shoe sensors. In Section 5, the experimental results with the proposed methods are presented and in Section 6, we conclude the paper with a summary.

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2. RELATED WORK

Early work on using acceleration sensors in activity recognition [16] proposes normalization and analysis strategies for human activity recognition based on a wearable device. In similar spirit, [2] presents activity recognition based on many three-axis acceleration sensors with similar accuracies. In [14], wearable sensors are presented as a general approach to gather data inexpensively. This data can be used to determine the user's location, detect transitions between preselected locations, and recognize the current activity, such as sitting, standing, and walking behavior. In contrast to the general work on activity recognition, our work is concentrated on the analysis of gait patterns. The authors in [18] present a versatile human-computer interface for the foot. The shoe includes various sensors to measure the person walking and running. Their shoe include pressure sensors in the insoles of the shoe, as does the present work.

Automatic segmentation method for body sensor data is presented in [8] that distinguishes between periods of activity and rest. In [13], the authors estimate dynamic parameters within the gait cycle. The authors in [12] present smart shoes that measure the ground contact forces and aim to detect abnormalities in the pressure patterns. They also present normal gait data patterns with sensor placement very similar to the current investigation. Gait-phase detection with sensor embedded in a shoe insole has been presented in [17]. They use four abstracted states in walking: Heel Strike, Swing, Heel Off, and Stance and present different transitory possibilities between the states. In [5], the authors present a six state left-to-right Hidden Markov Model to model gait patterns. The authors in [19] present different configurations of active pressure sensors in the shoe, and select the best configuration among the set of configuration patterns with the same number of active sensors.

Early review on human balance and posture control [21] identifies an inverted pendulum model of a human being as the common denominator in the assessment of human balance and posture. In contrast to such physics-based models, we model the distribution of sensor data in order to yield compact and understandable patterns [11].

3. BODY SENSOR RECORDINGS

We use body sensor recordings in a controlled walking experiment, which has been documented in our previous publication [15]. The time series collection has been made publicly available. In the experiment, the study subjects are asked to walk forward and backwards on a line on a track in a controlled fashion. The study subjects wear acceleration sensors attached to their body. There are three-axis acceleration sensors in the upper back, lower back, both knees and ankles, as well as pressure sensors in the shoes. In the current contribution, we will solely concentrate on the pressure sensor measurements, measuring the impact of the bottom of shoe hitting the ground when walking.

The pressure sensor measurements in the insoles of the shoes are now described in more technical detail. There are four sensors measuring pressure on a quantitative scale. The sensors are located in the heel, two in the metatarsal head region (inner and outer side), and toe region. The sensor measurements have been recorded with 8-bit accuracy and represented as integers ranging from 0 to 255. For the purposes of deriving binary patterns, which we will subsequently analyze, we threshold the data to yield 0-1 data. The choice of the threshold may vary, for instance, we may opt to use the median of the data distribution to yield dense representation of patterns. We expect that using a low threshold will result in dense and somewhat noisy patterns, whereas a higher threshold will result in sparse, but maybe not so rich patterns in the data. There is a trade-off to be made in selecting the representation of data. In the experimental part, we have used the 60th percentile of each pressure sensor data distribution to threshold the raw sensor values. Any value exceeding this value will yield a binary measurement 1 and consequently, any value less or equal will result in a 0 value. The threshold values are estimated for each sensor separately to accommodate for possible differences in the sensors themselves. The trade-off of selecting a threshold value is illustrated in Figure 1, where we illustrate the nature of the binary time series data. The percentiles are calculated from the sensor-specific distributions. The figure illustrates the varying degree of sparsity when different percentile thresholds are used. This presents a challenge for identifying patterns from data: in modeling, we must select the representation is the most suitable for descriptive patterns of data. Rather that concentrating on the selection of the thresholding values, we work with the data set that is rich enough to have the dependencies present in the data and model the data with a probabilistic model.

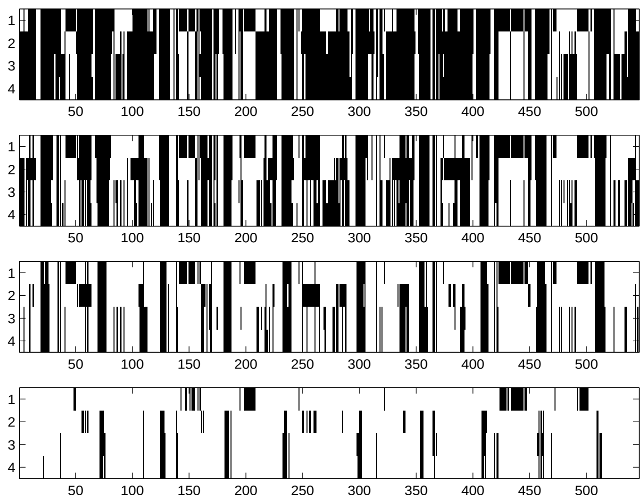

Figure 1: Example of walking patterns expressed with binary data as a result of thresholding the original sensor data represented as 8-bit integers. The time is represented on the x-axis, the readings of four sensors in the insoles of the shoes are depicted as four separate columns on the y-axis. The difference between the panels is that we have used different values of thresholding to yield the binary patterns. From top panel to bottom panel, 30th, 50th, 70th, and 90th percentiles are used for thresholding.

4. ANALYSIS OF GAIT PATTERNS

We approach the problem of gait analysis in the framework of data mining [9] since the data are represented in the form of 0-1 data vectors. Arguably, there are temporal dependencies in the data, but we essentially ignore the temporal dependencies and concentrate on modeling the marginal distributions of the four-dimensional binary data. Furthermore, we assume independence of the sensor recordings within one data vector. We approach the modelling with finite mixture models of multivariate Bernoulli distributions [22] and use the BernoulliMix program package [10] in the experiments. The mixture models assume a generative model, in which the observations are conditionally independent given its parent variable, which is latent [3]. This is a similar assumption as in Naive Bayes models, the only difference being that Naive Bayes models usually assume that the of the parent, or class variable is observed. We denote the data vector at time t containing the four sensor measurements by $\mathbf{x}_t = [x_{t1}, x_{t2}, x_{t3}, x_{t4}]$. In this work, we consider the realizations of the random variables observed in time to be independent. Although somewhat contrary to intuition, this is still a viable assumption and simplifies the model considerably. The joint probability distribution of the finite mixture model is factorized as presented in the following equation

$$P(S_1,\ldots,S_T,\mathbf{x}_1,\ldots,\mathbf{x}_T)=\prod_{t=1}^{T}P(S_t,\mathbf{x}_t)=$$

$$\prod_{t=1}^{T}\sum_{j=1}^{J}P(S_t=j)P(\mathbf{x}_t\mid S_t=j)$$

$$\prod_{t=1}^{T}\sum_{j=1}^{J}P(S_t=j)\prod_{i=1}^{d}P(x_{ti}\mid S_t=j).$$

The model parameters can be estimated with the Expectation Maximization (EM) algorithm [22, 7]. The EM algorithm estimates the maximum likelihood parameters from the incomplete data. The parameters are the mixing coefficients $\pi_j = P(S_t = j)$ and the parameters of the component distributions $\theta_{ji} = P(x_i \mid S_t = j)$. Before training can take place, the number of mixture components J must be decided. The issue of model selection — selecting an appropriate number of mixture components — has been dealt with in our previous publications [20]. In this paper, we set the number of mixture components to be $J = 4$, according to the knowledge in the gait analysis domain. Other researchers have presented their choices in selecting the complexity of the model. Gait-phase detection with sensor embedded in a shoe insole has been presented in [17]. They use four abstracted states in walking: Heel Strike, Swing, Heel Off, and Stance and present different transitory possibilities between the states. In [5], the authors present a six state left-to-right Hidden Markov Model to model gait patterns. The authors in [19] present different configurations of active pressure sensors in the shoe, and select the best configuration among the set of configuration patterns with the same number of active sensors. For us, it is interesting to see the interpretability of our findings in light of the already suggested gait models, which leads us to prefer a smaller number of component distributions to explain the data. In our previous research, we have described mixture models in compact and understandable form by deriving cluster-specific patterns [11].

5. EXPERIMENTS

We extract pressure data indicating the contact with the bottom of the shoe with the ground from the left shoe in the experiment, where study subjects walk forward in a controlled experiment. We use the 60th percentile of sensor-specific readings in each walking experiment as a threshold to get binary walking patterns. The matter of thresholding was illustrated with different threshold values in the Figure 1. Consequently, we train initially five mixture models from the training data, and calculate the likelihood values from training data and validation data sets. We select as our final model the one that has the best fit according to the validation likelihood. The mixing coefficient of the identified mixture model are in Table 1 and the parameters of the component distributions are in Table 2.

Out of the four mixture components, the second is the most dominating pattern in the data, followed by the fourth and the third. The first component distribution models only about 10 percent of the data distribution. We can give an interpretation to the patterns generated by the model by observing the corresponding probability parameters. The most dominating component, the second component distribution ($J = 2$), models the heel pressing down onto the floor

Table 1: The mixing proportions in the mixture model. Mixture coefficients correspond to the prior probabilities of the component distributions.

$\pi_1 = 0.101$	$\pi_2 = 0.517$	$\pi_3 = 0.164$	$\pi_4 = 0.218$

Table 2: The parameters of the component distributions in our mixture model with four component distributions. The first row has the generative probabilities of the four sensor readings (0/1). The dimensions are heel, two sensors in the middle part (metatarsalis head area), and the fourth in located in the toe area.

$\theta_{11} = 0.163$	$\theta_{12} = 0.387$	$\theta_{13} = 0.067$	$\theta_{14} = 0.114$
$\theta_{21} = 0.315$	$\theta_{22} = 0.123$	$\theta_{23} = 0.000$	$\theta_{24} = 0.001$
$\theta_{31} = 0.222$	$\theta_{32} = 0.495$	$\theta_{33} = 0.997$	$\theta_{34} = 0.983$
$\theta_{41} = 0.816$	$\theta_{42} = 0.966$	$\theta_{43} = 0.999$	$\theta_{44} = 0.988$

(probability of the first dimension is high), and partially the inner metatarsalis being pressed (also, the probability of the second dimension is relatively high). The component distribution ($J = 4$) models all four sensors being in firm contact with the floor. The third component distribution ($J = 3$) models firm contact with the floor in the toe part and the outer side of the metatarsalis area and moderately firm pressure in the inner metatarsalis sensor, which can be identified as a gait phase of its own. It is more difficult to give a clear interpretation to the component distribution $J = 1$, which in effect may model the rest of the probability mass in the data.

6. SUMMARY AND CONCLUSIONS

Sensory information can be used for activity recognition and remote monitoring of the elderly. Analysis of gait, or person's manner of walking, has been subject to active research, using various modes of gathering data from the study subjects. In this paper, we focus on the walking patterns measured with four pressure sensors in the bottom of the shoes to measure contact between the shoe and the ground. This data is a part of publicly available time series collection of body sensor recordings. We transform the original, raw data by thresholding it with a data-derived threshold and output binary 0-1 data indicating contact between the shoe and the ground with binary truth values. We model the data with a mixture model of Bernoulli distributions with four component distributions, where the complexity of the model is set according to the domain expertise of the gait cycle. The model has a simple interpretation in terms of the sensor contacts with the floor, and correspond to the gait cycles of the foot hitting the floor, with the pressure gradually moving towards the toes while the step proceeds.

We have modeled the marginal distributions of the gait patterns with finite mixture models of multivariate Bernoulli distributions. For simplicity, we have not made explicit use the sequential dependency between the time steps. It would be interesting to model the sequencing of the probabilistic step patterns in the data, with modeling the temporal dependencies with Markovian models [4] such as Hidden

Markov Models (HMM). To relate model selection procedures to setting the model parameters with domain knowledge also is an interesting and important issue.

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