Probabilistic modelling of gait for remote passive monitoring applications

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Abstract

Passive and non-obtrusive health monitoring using wearables can potentially bring new insights into the user’s health status throughout the day and may support clinical diagnosis and treatment. However, identifying segments of free-living data that sufficiently reflect the user’s health is challenging. In this work we have studied the problem of modelling real-life gait which is a very indicative behaviour for multiple movement disorders including Parkinson’s disease (PD). We have developed a probabilistic framework for unsupervised analysis of the gait, clustering it into different types, which can be used to evaluate gait abnormalities occurring in daily life. Using a unique dataset which contains sensor and video recordings of people with and without PD in their own living environment, we show that our model driven approach achieves high accuracy gait detection and can capture clinical improvement after medication intake.

1 Introduction

Sensors embedded in smartphones and wearables can provide valuable information about the health status of patients with various movement disorders [1]. Most research has focused on analyzing standardized assessments in controlled environments [2]. When deployed in the patient’s own home environment, wearable sensors could be used to passively record real-life symptom fluctuations [3]. This could provide physicians and patients with additional information about the progression of the disease and the efficacy of treatment, even without the need for hospital visits. The modelling challenge this introduces is how to deal with the enormous variation in real-life signals, which is not only influenced by the patient’s condition, but also by the large variation in daily life behaviours. One approach is to analyze behaviour that is common across patients and likely to reflect the status of the patient’s condition. An important example of such behaviour is gait, a highly prevalent and stereotypic behaviour, which is known to be indicative of several neurological conditions, such as Parkinson’s disease (PD).

There is a plethora of prior work focused on analysis of gait using accelerometers and gyroscopes [4,5,6,7]. Most algorithms consist of two separate steps, i.e. gait detection and for quantification of the gait pattern. The detection phase normally aims to segment out all activities which involve walking while the further analysis of these segments is done to discover periods of gait and gait properties indicative of user’s health. Gait detection is often done using supervised learning or thresholding techniques, applied to simple features extracted from a moving window of fixed width. Commonly used features include standard deviation [8,9,10], Fourier coefficients [11,12,13] and normalized autocorrelation [14]. Hand tuned thresholds can be avoided by training classification methods such as Support Vector Machines (SVMs) [15], Naive Bayes or 2-component Gaussian
Hidden Markov Models (HMMs) [16,17]. From the identified gait, properties such as step time and step length can be estimated to describe the quality of the user’s gait. These methods, often developed for specific body locations, rely on identifying specific peaks that correspond to the initial and final contact of the gait cycle [18,19,20]. Less location-specific are spectral methods that look at the leading harmonics [4] and autocorrelation methods that measure autocorrelation at certain lags [14].

Most of the methods for both detection and analysis of gait are validated on labeled datasets that only include a restricted set of activities performed in controlled environments. Because of this and their lack of rigorously dealing with uncertainty, such methods have to hard to analyze behaviour when applied to data collected in daily life, where an arbitrary large number of different activities can be recorded. Whereas some empirical prove of accuracy might be sufficient in consumer applications, medical applications require highly interpretable algorithms that can generate reliable and verifiable insights in daily life gait patterns.

In this work our objective is to jointly detect and analyze gait patterns combining previously proposed ideas into a robust model based framework for analysis of real-life gait data. Our approach extends existing HMM techniques by adopting a nonparametric framework that allows us to infer different gait and non-gait states from the data in an unsupervised way. Also, we propose using an autoregressive observation model to describe each state. We demonstrate our approach on a new unique reference dataset consisting of sensor data from various wearables and concurrent video annotations, collected in the home environment of people with and without Parkinson’s disease (PD).

2 Probabilistic modelling of gait

In this section we layout the minimalistic assumptions that we embed in our probabilistic model for analysis of gait data from wearable accelerometer sensors. We do not extract many types of correlated features that are hard to interpret but we attempt to model a minimal amount of features (the acceleration amplitude) and account for some of the common confounding factors occurring in data recorded by inertial measurement units. This more direct model-driven approach to gait analysis is less reliant on labeled data which is an essential requirement for future tools for passive monitoring.

Pre-processing: Accelerometer data collected from different smartphones is sampled at non-uniform rates varying from approximately 30 to 200Hz. Therefore, data is interpolated to a uniform rate and further downsampled (using standard anti-aliasing moving average filter) to 30Hz, which is sufficient to measure human gait [21]. Accelerometers are heavily confounded by changes in the orientation of the device irrelevant to the user’s gait. In order to remove this undesired effect of gravity, we use a L1-trend filter [22,23] to estimate a piecewise linear vector which is then subtracted from the accelerometer data. Finally, we model the amplitude of the remaining dynamic component which we can denote as a 1-D series \( x_1, \ldots, x_T \).

Capturing the rhythm of gait: Natural human gait is highly repetitive as it consists of multiple consecutive gait cycles. As a result, the accelerometer signal during gait is generally highly periodic. However, many other periodic and non-periodic movements occur in free-living human behaviour. To model free-living gait, we need both high frequency resolution to capture underlying patterns of gait and precise time localization of when gait starts or stops. This is hard to achieve in the Fourier domain and we usually sacrifice time localization accuracy. But if we apply a sequential switching state space mechanism, we can adaptively infer the start and end of the stationary intervals associated with the gait behaviour. Here we model the spectrum of the gait using autoregressive processes (AR).

An order \( r \) AR model is a random process which describes a sequence \( x_t \) (for \( t = r + 1, \ldots, T \)) as a linear combination of previous values in the sequence and a stochastic term: \( x_t = \sum_{j=1}^{r} A_j x_{t-j} + e_t \) with \( e_t \sim \mathcal{N}(0, \sigma^2) \) where \( A_1, \ldots, A_r \) are the AR coefficients and \( e_t \) is a zero mean, Gaussian i.i.d. sequence. An important property of AR models is that we can express its power spectral density as a function of its coefficients: \( S(f) = \frac{\sigma^2}{1 - \sum_{j=1}^{r} A_j \exp(-i2\pi fj)} \) where \( f \in [-\pi, \pi] \) is the frequency variable with \( i \) here denoting the imaginary unit. This means that the order of the AR model directly determines the number of “spikes” in its spectral density. We assume that with a high enough order \( r \), an AR model is a good summary of a particular type of gait [24]. Next we need a systematic way to infer when behaviours other than gait occur or when a different type of gait is being observed. To do this in sufficiently flexible manner, we couple the AR component with a nonparametric hidden Markov model [25,26] (more specifically: direct assignment HDP-HMM [26]).
to obtain a nonparametric switching AR process, which was first introduced in Fox et al. [27]. In nonparametric switching AR processes we assume that the data is an inhomogeneous stochastic process and multiple different AR models are required to represent the dynamic structure of the series, i.e.:

\[ x_t = \sum_{j=1}^{r} A_j^{(z_t)} x_{t-j} + e_t^{(z_t)} \quad e_t^{(z_t)} \sim \mathcal{N} \left( 0, \left( \sigma^{(z_t)} \right)^2 \right) \] (1)

where \( z_t \in \{1, \ldots, K^+\} \) indicates the AR model associated with point \( t \) and \( K^+ \) varies. The latent variables \( z_1, \ldots, z_T \) describing the switching process are modelled with a Markov chain. This Markov chain is parametrized with a transition matrix, the weights of which are modelled with a hierarchical Dirichlet process (HDP). This allows the number of represented states \( K^{+} \) to be inferred from the data where \( K^{+} \ll T \) allows us to cluster together data which is likely to be modelled with the same AR coefficients.

**Sparseness of the representation:** To finish our model, we specify a prior over the remaining unknown parameters, i.e. the AR coefficients and the process error. Since these can be seen as the parameters of a linear regression problem, the conjugate prior over \( \{A, \Sigma\} \) is a matrix Normal inverse Wishart prior which for univariate \( x \) collapses down to a multivariate Normal inverse Gamma prior: \( \{A, \Sigma\} \sim \mathcal{N}(A | \mu_0, \sigma \Sigma) \text{ Inv-Gamma}(\sigma | \nu, \theta) \). Despite of the numerical convenience of this prior, better control over the sparseness of the posterior coefficients can be obtained if we instead use a non-conjugate independent 0-mean Gaussian prior over each coefficient, \( A_j \sim \mathcal{N}(0, \sigma) \) for \( j = 1, \ldots, r \). In this way we can model the AR coefficients and error separately; we define a separate inverse Gamma prior over the process error: \( \sigma \sim \text{Inv-Gamma}(\nu, \theta) \) (this prior is referred to as automatic relevance determination prior in [28]). The effect of the two priors is compared visually on the same gait data in Appendix B.

![Figure 1: Estimated features c (red) and a + d (blue) for a responsive (top) and a non-responsive (bottom) PD patient. x-axis is time relative to medication intake; y-axis is feature values.](image)

## 3 Evaluation

We apply the proposed framework for model based gait analysis to data from the Parkinson@Home validation study (see Appendix C). In brief, 24 participants with PD receiving dopaminergic medication and 24 age-matched participants without PD were visited in their own homes. The visits included an unscripted free-living part of approximately 1 hour, in which the assessors encouraged the participants to perform usual activities. The PD group was instructed not to take their PD medication before the visit, in order to perform the free-living part both before and after medication intake. Participants wore various light-weight sensors and the full visits were recorded on video. In this work, we use accelerometer data from a smartphone worn in the front trouser pocket, and video annotations indicating the presence and impairment of gait.

By segmenting the accelerometer signal in an interpretable way, we aim to group various types of gait patterns and extract useful information about the gait. After the accelerometer data from the users’ smartphones have been appropriately pre-processed, we fit in an unsupervised way a nonparametric switching AR model of order \( r = 90 \) to the amplitude of the dynamic component. The nonparametric switching AR model adopts an additional parameter supporting self-transitions (using ‘sticky’ HDP)

\[ \text{One can further assume } \sigma \text{ varies across coefficients in order to place more importance on inferring patterns in the data that occur with specific lags} \]
and training is done using a novel streaming slice sampling method. Similar results were obtained if using truncated block sample from Fox et al. [27].

Our method can detect walking activities at least as well as other best performing benchmark heuristics (selected from [4]). Once we have trained the unsupervised switching AR on the data from the home visits, there are several ways of using either some domain knowledge or a small amount of supervised data to train a classifier which predicts if data corresponds to gait related activity or not. For example, here we train an interpretable multinomial Naive Bayes classifier (which is linear in the log space) in which the input is the posterior of $z_t$ for each point $t$ and the output is a binary indicator denoting if a point is associated with a gait activity. This approach relies on the assumption that most of the gait patterns would be clustered in their own states. The hyperparameters for all of the benchmarks are selected in-sample to maximize the balanced accuracy and demonstrate highest possible discrimination accuracy that these techniques can achieve on our new dataset. The standard deviation thresholding (highest performing benchmark for gait detection in [4]) scored sensitivity of 0.79 and specificity of 0.96; short-term Fourier transform gait detection scored sensitivity of 0.85 and specificity of 0.94; normalized autocorrelation step counting heuristics (NASC)[14] scored sensitivity of 0.87 and specificity of 0.94. The naive Bayes classifier just trained on the state indicators associated with each point achieved out-of-sample sensitivity of 0.85 and specificity of 0.97 with standard deviation of 0.05 on both the sensitivity and the specificity measures for different runs of the switching AR model.

In addition to identifying gait segments, the estimated AR parameters associated with the data can be used to quantify some properties of the observed gait. Given input sensor data of 30Hz sampling frequency, the $r = 90$ AR model estimates how well data lagged up to 3 seconds predicts itself, i.e. the AR model estimates the periodicity of the signal between bands of 0.33Hz and 30Hz. This means that information such as the duration of the gait cycle, the variability of the gait rhythm or its amplitude are already encoded in the inferred AR coefficients and error. For example, assuming that our AR coefficients are fairly sparse and the leading periodic component in the signal is due to the repetitiveness of the full gait cycle, we can fit a Gaussian polynomial $f(x) = a \exp \left(-\frac{(x-b)^2}{c}\right) + d$ to the AR coefficients to estimate both the expected time a gait cycle takes and how much this time varies (see Appendix A); if the location $b$ is at the 40th coefficients, this would indicate that the most likely cycle time is $\frac{40}{30}$ seconds; $c$ would reflect how much this cycle time varies for a particular AR state, and $a + d$ indicates the estimated value of $f$ at $b$ which reflects the support at the peak cycle time $b$.

We illustrate that the proposed features are highly related to medication-induced changes in the gait pattern in Figure 1, where we plot the value of $c$ and $a + d$ for the fitted polynomials against the time for two PD patients: one with clear clinically observable changes in his gait pattern, and one with no observable changes. In the first patient, we observe a consistent drop in the values of $c$, a consistent increase in the values of $a + d$ and a mild increase in $b$ (latter not plotted), whereas these changes are absent in the non-responsive patient. Future work will address how these features should be interpreted from a clinical perspective, and what are the most important confounders (factors other than the severity of PD symptoms) present in daily life that may influence the gait pattern analysis.

### 4 Conclusion

Recent technological advances have made it possible to remotely and continuously collect sensor data in daily life. Yet estimating features that provide reliable insights in a person’s health remains challenging. For movement disorders such as PD, analyzing free-living gait is a promising approach. Here we present a highly interpretable probabilistic framework that can robustly detect gait and group different gait patterns in PD patients corresponding with medication-induced changes. Advances in algorithms to analyze passively collected sensor data will hopefully provide novel insights in the real-life functioning of patients with PD, which will benefit both clinical trials and individual patient care.

**Acknowledgements:** This work was supported by the UCB Pharma, Michael J. Fox Foundation and Stichting Parkinson Fonds. The authors extend their sincere gratitude to every individual who participated in this study to generate the data used here.
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A  Interpretation of AR coefficients when modelling gait

Visual example of the AR coefficients inferred for a segment of free living gait. We fit a polynomial of selected form in red, where we have chosen a Gaussian polynomial of the form \( f(x) = a \exp\left(-\frac{(x-b)^2}{c^2}\right) + d \) and infer its best location according to the AR coefficient values. Here we have done least squares polynomial fitting, but in the future this step can also be done by Bayesian polynomial fitting.

B  Sparse vs non-sparse prior choice over the AR coefficients

Visual comparison of the effect of non-conjugate sparse prior and conjugate prior on the posterior of the AR coefficients estimated by fitting an AR model on the same free living segment of gait using Gibbs sampling.

C  Parkinson’s® Home validation study - description

Data used in this work was obtained from the Parkinson@Home validation study, which was conducted at the Radboud University Medical Centre, Nijmegen, The Netherlands. In collaboration with the Michael J Fox Foundation, a reference dataset will be made accessible to the research community. The study included 25 participants diagnosed with Parkinson’s disease and 25 age-matched participants without Parkinson. Inclusion criteria consisted of: (1) age \( \geq 30 \) years and (2) in possession of a smartphone running on Android 4.4 or higher. Additional inclusion criteria for the Parkinson group were: (1) diagnosis of Parkinson, (2) treated with levodopa and/or a dopamine agonist, (3) experiencing motor fluctuations (MDS-UPDRS item 4.3 \( \geq 1 \)), and (4) known with bradykinetic gait and/or freezing of gait (MDS-UPDRS item 2.12 \( \geq 1 \) and/or item 2.13 \( \geq 1 \)). Candidates who received any advanced treatment were excluded. All participants provided written informed consent and the study protocol was approved by the local ethics committee (Commissie Mensgebonden Onderzoek, Arnhem-Nijmegen; NL53034.091.15). Data was collected during home visits in the morning, which
included an unscripted free-living part of approximately 1 hour, in which the assessors encouraged the participants to perform usual activities. To make sure essential behaviors were captured, such as longer gait cycles, assessors encouraged participants to include these in their routines. The Parkinson group was asked to skip their morning dose of dopaminergic medication before the visit. The free-living part was repeated after medication intake. During the full visit, participants wore various light-weight sensors on both wrist, both shins, the lower back and in the front trouser pocket. In this work, we used the accelerometer data obtained from the smartphone worn in the trouser pocket. The complete visits were recorded on video, which were annotated by a research assistant for the presence of walking episodes, which were defined as any activity including at least 5 consecutive steps, excluding stair climbing and running.

Currently, data was available for 48 participants because of data quality issues in 2 participants: one smartphone sensor malfunctioning and one problem with the video recordings.