Abstract

Gait analysis can be a valuable tool in medical research and the diagnosis of certain pathologies, by delivering important information that helps in choosing an intervention and rehabilitation pathway that is most beneficial for a patient. In specialised gait laboratories, technical sensors such as cameras or inertial measurement units are often used to gather relevant gait data. This thesis now contributes to the field of sensor-based gait analysis by exploring the possibilities of using sensors below the floor as a gait data source. These sensors measure changes in the electrical capacitance to recognise steps. A framework was developed to formalise representations of the floor sensor measurements, taking into consideration the special characteristics of the data that are delivered by the sensor floor. The resulting data representations were used as input for various artificial neural network models that were applied to perform classification and regression tasks. In this process, two distinct methods were used: First, in a feature construction and extraction approach, a feature vector containing the spatial spread of footfalls was derived and used as input to a feed-forward neural network. Second, in a feature learning approach, the time series data was transformed into a local receptive field, and thereby directly used as input to a recurrent neural network.

The floor sensor is a construction that is designed to be used in indoor environments and is hidden under common flooring layer types. This makes it very robust and thereby suitable for practical use, even in daily clinical routine where there is no leeway to take care of potential fragilities of sensors. It also provides an alternative approach for gait analyses in the context of elderly care, where much focus has to be devoted to the handling of the patient, and unobtrusive medical tools are especially beneficial. For the goal of training artificial neural networks, it was needed to find different representations of the sensor floor data, as the properties of the data that can be recorded in this way are not similar to other types of sensor data for which representations are well known. The application of machine learning for analysis is a particularly useful approach for sensor data, as valuable information is hidden in the patterns of the often huge amounts of data. Three studies were conducted, showing that this methodological combination can be applied to concrete gait analysis scenarios: It was investigated, with very satisfactory results, if it is possible to 1.) distinguish between people with low and high risk of falling, 2.) estimate age, and 3.) recognise walking challenges as an external gait intervention. The combination of a robust and hidden floor sensor and machine learning data processing opens up the prospect of future applications in health and elderly care.

Zusammenfassung

Die Ganganalyse ist ein wertvolles Werkzeug in der medizinischen Forschung und Diagnose mancher Krankheiten, da sie mit wichtigen Informationen dabei unterstützt, über die Art der Intervention und Rehabilitation zu entscheiden, die für einen Patienten am vorteilhaftesten ist. In spezialisierten Ganglaboren werden oft technische Sensoren wie Kameras oder Inertialsensoren eingesetzt, um relevante Gangdaten zu sammeln. Die vorliegende Arbeit leistet einen Beitrag zum Bereich der sensorbasierten Ganganalyse, indem Möglichkeiten erforscht werden, Sensoren unter dem Fußboden als Quelle für Gangdaten zu nutzen. Dieser Sensortyp misst Änderungen der elektrischen Kapazität, um Schritte zu erkennen. Es wurde ein Framework zur Repräsentation der Bodensensormessungen entwickelt, das die speziellen Eigenschaften der Daten, die der Sensorboden liefert, berücksichtigt. Die resultierenden Datenrepräsentationen wurden als Eingabe für verschiedene Modelle von künstlichen neuronalen Netzen für Klassifikations- und Regressionsaufgaben verwendet, wobei zwei Ansätze verfolgt wurden: Zunächst wurden in einem Merkmalskonstruktions und -extraktionsverfahren Merkmalsvektoren abgeleitet, die die räumliche Streuung von Schritten enthalten, und als Eingabe für vorwärtsgerichtete neuronale Netze verwendet wurden. Als nächstes wurden Merkmale direkt gelernt, indem die Zeitreihendaten in ein lokales rezeptives Feld transformiert und dann direkt als Eingabe für ein rekurrentes neuronales Netz verwendet wurden.

Der Sensorboden ist eine Konstruktion, die für den Einsatz in Innenräumen konzipiert ist und die unter üblichen Bodenbelägen verbaut wird. Das System ist dadurch sehr robust und damit geeignet, in der Praxis eingesetzt zu werden - selbst im klinischen Alltag, wo wenig Raum zur Rücksichtnahme auf fragile Sensoren vorhanden ist. Für das Ziel, künstliche neuronale Netze zu trainieren, war es notwendig, verschiedene Repräsentationen der Sensorbodendaten zu finden, da die Eigenschaften der so aufgenommenen Daten nicht mit anderen Arten von Sensordaten vergleichbar sind, für welche solche Repräsentationen bereits bekannt sind. Die Anwendung von maschinellem Lernen zur Analyse ist vor allem für Sensordaten ein sinnvoller Ansatz, da sich in den Mustern der oft riesigen Datenmengen wertvolle Informationen verbergen. Es wurden drei Studien durchgeführt, die zeigen, dass diese Methodenkombination im Kontext der Ganganalyse angewendet werden kann: Mit sehr zufriedenstellenden Ergebnissen wurde untersucht, ob es möglich ist, 1.) zwischen Personen mit niedrigem und hohem Sturzrisiko zu unterscheiden, 2.) das Alter zu schätzen und 3.) beim Gehen auferlegte Herausforderungen als externe Intervention zu erkennen. Die Kombination aus einem robusten und versteckten Bodensensor und Datenverarbeitung mittels Maschinellen Lernens eröffnet die Möglichkeit zukünftiger Anwendungen in der Medizin und Altenpflege.

Chapter 1

Introduction

The central topic of this thesis is situated at the intersection of the scientific disciplines of machine learning, sensor technology, and gait analysis. Within the research area opened up by this interdisciplinary overlap, the goal was set to develop methods to apply machine learning techniques to a special kind of sensor data, namely data generated by a sensor floor with some unique characteristics and properties compared to other types of sensor data. The use of machine learning methods on this exact kind of floor sensor data is an approach that was not yet applied before at all.

As an important required step, a mathematical framework was developed with the goal to formally represent the sensor data such that it can be used with machine learning algorithms. Thereby, the framework closes the gap between the special format of the data that is delivered by this sensor system and the typical formats that are necessary to present data as an input to common machine learning algorithms and model types like artificial neural networks. The methods that were developed to enable the analysis of such kind of data by application of machine learning algorithms were then evaluated on several gait analysis tasks. For this, the walking patterns of people walking on top of the floor were recorded. The effectiveness of the system was demonstrated in three studies with different objectives: 1.) classifying between people at risk of falling and those who are not, 2.) estimating the age of a person, and 3.) recognizing various walking challenges imposed on young healthy adults.

Methods of machine learning have already shown their value in the analysis of data generated by various other technical sensors. A common example of such data is found in the form of images, which are delivered by camera sensors. When analysing images, may it be by the application of machine learning or other approaches of computer vision, the goal is often to recognise something that is seen by the camera and thereby captured on the image. Machine learning methods, and from those especially artificial neural network algorithms, produce very good results on such tasks, and they show continuous improvements in becoming more robust and understandable. Examples of such models are, among others, the *Overfeat* model [Ser+13], the *DeepMultiBox* model [Erh+14; KSH12], or the *YOLO (You only look once)* model [Red+16] with its variations [Mao+19; Sha+17] and updates [RF17; RF18]. The high performance of these models is to a substantial part attributed to the fact that they all include a special kind of artificial neural network model that is exceptionally well suited for the sensor characteristics, which, for image data, is the convolutional neural network [LB95]. The convolutional neural network works so well for image data as its input is formatted as regular (euclidean) grids with square-shaped boundaries which are shifted, or slided over data which is also shaped as a grid, making the model somewhat similar to a convolutional operator in signal analysis. In the 2-dimensional case, this fits perfectly to image data, which is typically present as a set of pixels, which are by themselves approximately a regular grid.

For other kinds of data, like from sensors that deliver data as a time series, other models are more suitable. Time series data is, for example, delivered by microphone sensors, with speech recognition as the primary objective. Here, again artificial neural networks showed to be very effective [DHK13; DP14; GMH13; Zha+18], in particular such artificial neural network models with recurrent architectures. As another example, inertial measurement units (IMUs) are also kinds of sensors that deliver time series data, by means of accelerometers and gyroscopes (and sometimes also magnetometers and barometers) for tracking motion in multiple dimensions, which can be used for a wide variety of applications. One area of application of IMUs is in human activity recognition [Li+18; Nis+20].

IMU sensors are small enough to put them into wearable devices, which makes it feasible to create data sets for applications in the area of human movement analysis. They are also used in gait analysis with machine learning methods [Aha+20]. For time series data, there is, besides many other models, again an artificial neural network model that fits very good to the data being a sequence, which is the recurrent long-short term memory architecture [HS97]. Recurrent connections in these models and architectures enable the network to carry inputs forward in time for the next iteration, or viewed the other way round, can access past inputs and past internal states from the model in the current iteration. This way, the model gains the capability of having a memory of the past. As valuable information in time series data is often hidden as sequential patterns, this property of having a memory makes recurrent models so useful for this kind of data.

If the data has characteristics of both image and time series data, like in video data analysis, convolutional, recurrent and other models can be combined as layers in a joint composite architecture to get the best of all worlds. Such models can, for example, be used for gait analysis [FLL16], but also for other applications where information should be extracted from video data. From these examples, one can see that technical sensors offer a lot of ground for useful analysis in all kinds of application scenarios when combined with fitting and well-designed machine learning architectures. Seemingly, every kind of sensor data can somehow be used meaningfully with machine learning methods, when the models fit good to the data properties and therefore the sensor characteristics.

In a medical context, specialised sensors come into use that collect physiological signals from the human body, which contain information on individual properties and conditions. To name just a few, these sensors measure values like the heart and respiratory rate, skin conductivity or blood glucose level. From this area of measuring states of the body, gait analysis focuses on the movements of the human musculoskeletal system components that are used for walking. These movements are typically described formally by parameters like step lengths and widths, the cadence, or joint angle changes over time [Bon+19a; Men+04; OKO93]. Physicians and therapists can use these parameters to diagnose diseases of the walking apparatus [Bea+17], or to track the healing progress of a patient after an injury [Ros+14]. Further, these parameters are useful to deliver early hints for emerging diseases [KH20; Rui+21]. To obtain these gait parameters, technical sensors can be used: They can be assessed with cameras by tracking joint and limb positions in the images or videos, or by IMUs which are attached to the joints and limbs of a person and which measure relative positional changes. For retrieving the subset of gait parameters that can be derived from step positions, one can also use sensor floors as a signal source. Sensor floors are generally more unobtrusive as nothing needs to be attached to the person and there is no need to keep a line of sight clear of obstruction as is the case with camera sensors. Floor sensor data cannot only be used for a direct parameter extraction for further analytical use with classical statistical procedures, as it is common in many research lines of gait analyses, but again also as input to machine learning models for classification and regression tasks.

In the research that was conducted for this thesis, such a floor sensor system is used, but one of an unusual kind that is under-represented in research literature on machine learning and gait analysis: This specific system is called *SensFloor* and measures the electrical capacitance on an array of many independently operating sensors below the flooring. This way, it can be integrated into any indoor environment and be used to track walking people and determine the positions and timings of their steps. The construction of this special sensor system results in some unique characteristics of the data when compared to other sensors, as it has the properties of non-rectangular discrete areas of measurement and an operating mode that works by an event-based delivery of signals. This means that the raw data cannot efficiently be taken as-is and directly serve as input to train a machine learning model of the common architectures, as there is no naturally fitting architecture like it would be the case with the convolutional neural network for image data, recurrent architectures for time series data or multi-layer perceptrons (also known as densely connected layers) for data sets that take the form of a set of vectors of fixed dimension.

This thesis elaborates on ways to use the floor sensor data with artificial neural networks, by taking into special consideration the unique properties of the floor sensor and then applying the derived methods to gait analysis. Considering the successes achieved with other sensors and machine learning methods for so many purposes, this work aims to contribute to machine-learning-based sensor data analysis by combining a new sensor with new data pre-processing and existing machine learning models for gait analysis.

1.1 Motivation

Contemporary research and the availability of vast and affordable computing resources showed that machine learning methods applied on data that is produced by all kinds of different sensors can lead to entirely new and powerful applications. At nearly the same time, the floor sensor that was used for the research in this thesis was developed and became available as a totally new kind of sensor and data source for human movement and behaviour. This general scientific advancement regarding both hardware (floor sensor technology, affordable high-power computing) and software (machine learning algorithms) led to the endeavour that resulted in this thesis: to pursue research into the direction of targeting combinations of floor sensor data and machine learning, and subsequently evaluating the resulting models and systems for specific uses, which is here done for the purpose of gait analysis. In the following it will be further elaborated on the three main points of the motivation for this thesis: First, the use of machine learning methods showed in general to be very suitable for sensor data analysis for other kinds of sensors