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Towards Inertial Sensor-Based Position Estimation in Bouldering

Tom Koller[1], Tim Laue[1] & Udo Frese[1]

[1]University of Bremen, Department of Mathematics and Computer Science, Bremen, Germany

Abstract

For some years, inertial sensors have become increasingly popular in various sports applications due to their small size and weight. However – due to the problem of sensor drift – additional sensors are usually required to obtain reliable position estimates. In this paper, we present an approach for position estimation in bouldering that relies solely on inertial sensors and domain knowledge that is modeled as a virtual sensor.

Keywords: Bouldering, Inertial Sensor, Position Estimation, Sensor Fusion

Introduction

Inertial Measurement Units (IMUs) in general integrate sensors for measuring accelerations, rotational velocities, and the magnetic field on three axes. In common sports applications, these measurements are analyzed directly or are used as input for classificators, which recognize different activities or sports-specific motion patterns. In theory, given a known starting position, one could integrate IMU measurements over time and thereby estimate the trajectory of a moving sensor, an approach known as dead reckoning in inertial navigation systems. However, due to accumulating errors, after some time, this process inevitably leads to wrong position estimates. Especially in MEMS-based sensors, which are the ones that are suitable for sports, significant errors might already occur after some seconds. Thus, any IMU-based trajectory estimation is only realizable for short motion sequences, such as weight lifting or the analysis of single stroke motions, e.g. in golf or tennis. Whenever motions are supposed to be tracked over longer time intervals, one has to add additional sensors, defeating the advantages of IMUs regarding size and weight.

In the project *ZaVI* („Zustandsschätzung allein durch Vorwissen und Inertialsensorik" / „State Estimation Solely based on Prior Knowledge and Inertial Sensing"), we investigated the concept of using prior knowledge about the application domain as an additional input for the estimation process to keep the accumulating errors within bounds. An initial successful sports application of this approach was track cycling, published by Koller et al. (2020). Here, knowledge about the track geometry and the driving behavior of a bicycle allowed to continuously estimate the position of track cyclers over many rounds.

In this paper, we describe the integration of so-called *event-domain knowledge (EDK)* for tracking the positions of the hands of a boulderer along a route. In this context, the EDK consists of known starting holds, a map of the route, and the fact that bouldering consists of a sequence of detectable events, i.e. the gripping of holds. This paper complements a recent publication by Koller et al. (2022) that describes the sensor fusion fundamentals of our approach in detail. In this paper, we focus on the actual sports application and discuss the potential of an inertial sensor-only tracking approach. The approach has been evaluated in a study involving 27 participants. The source code as well as the data gathered during the study has been released as Open Source by Koller (2022), including videos of the trials as well as ground truth data recorded by an external tracking system.

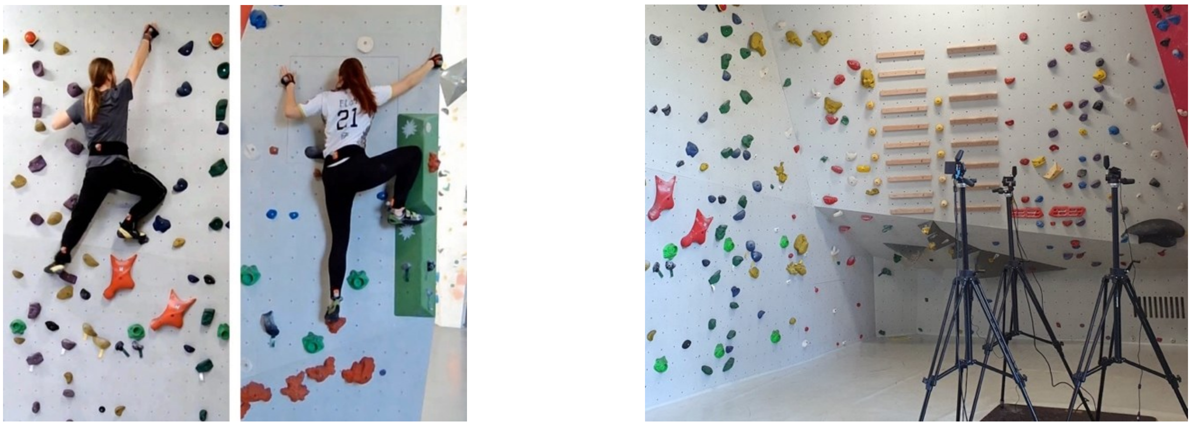
Methods

The implemented approach estimates the position of a single inertial sensor. For the bouldering application, a sensor is attached to the back of each hand of a climber, roughly comparable to the position of a smartwatch or a fitness tracker. They are treated as fully independent of each other. Furthermore, no skeleton model or any other user configuration is used. The two start holds are assumed to be known, as these are usually explicitly marked at a typical bouldering route. However, it is not known, which hand is at which hold. The approach consists of following three components:

The *grip detector* uses the raw inertial sensor data to detect the moments, in which the climber grips a hold. For this purpose, different implementations already exist. In our work, we use the approach by Ladha et al. (2013). The detection of the gripping events allows us to divide the whole climbing process into a sequence of phases of free sensor motion and phases in which the hand (and thus the sensor) is almost fixed at a hold.

The *transition estimation* provides a position estimate given the position of the last hold and the sum of all IMU measurements until the next gripping event is detected. Currently, a least squares optimization over these measurements is performed to determine the transition. However, as described in the Discussion section, faster approaches are generally applicable for this task, too. Compared to existing route classification systems, this approach computes a full trajectory of the sensor between two holds and thus provides more comprehensive motion information for a possible later analysis instead of a mere sequence of holds.

Finally, the grips as well as the transitions are used as an input for a *particle filter* that incorporates the event-domain knowledge for the sensor position estimation. The particle filter approach has been chosen as it suits best to a domain, in which discrete gripping events and multimodalities such as sets of probable holds (on a bouldering route, the climber is free to decide about the sequence of the used holds) need to be modeled. We use a standard particle filter implementation. To improve precision, a particle filter smoother, as described by Doucet and Johansen (2011), is used. A detailed formal description of our approach is given in Koller et al. (2022). The event-domain knowledge consists of the detected gripping events and a previously created map of the bouldering route. In the map, the actual shape of a hold is not modeled, but just its position on the wall. However, in general, the used approach would allow an integration of such shapes, which would be a necessity for routes incorporating huge macros, for instance. This would require a different distance measure, based on dynamically generated contact points. In the current version, this has not yet been realized to keep the generation of map data manageable and the gripping distribution simple. Whenever a gripping event is detected, the most likely hold is determined and each sample's weight is set accordingly. Touching or holding the wall is possible, too. This is handled by using a uniform distribution with a constant likelihood.



(a) (b)

Fig. 1 (a) Two of the routes used for the evaluation, the climbers wear gloves with attached sensors. Additional sensors were attached to the tailbone and the heels, but not used for the work presented in this paper; (b) The setup for obtaining ground truth data and video recordings.

Results

For the evaluation of our approach, a study with 27 participants (6 female, 21 male) was conducted at the DAV-Kletterzentrum Bremen, a professional climbing venue. The participants, who all had at least some experience regarding bouldering, climbed 12 different routes, some of them are depicted in Fig. 1a. Some routes were climbed multiple times, resulting in a total 775 valid trials of the left hand and 769 of the right hand. The routes were of different difficulty (within amateur level) but all located on normal vertical walls, i.e. without any major overhangs and complex volumes, which would, however, not oppose our approach in general, as long as the geometry is known. Furthermore, the routes, except for one, did not require any dynamic moves such as jumps.

The approach does not rely on any specific inertial sensor. For our experiments, we used XSens MTw Awinda sensors, which are robust and reliable and which allow a wireless data transfer. For obtaining ground truth information, an ART TrackPack system with two cameras was used (see Fig. 1b). The system requires markers that we attached to the sensors. The ART provides millimeter precision ground truth data, but is subject to occlusions by body parts. The experimental results were obtained offline on recorded datasets, which contain inertial sensor data, synchronized with ground truth and videos.

The data of 4 participants has been used for the development and tuning of the approach, the data of the other 23 was used for evaluation. Over these datasets, the median position error of a sensor, compared to the ground truth information, was 0.132 m. When not using the particle filter smoother but a standard particle filter, the error was 0.145 m. In contrast, when not using the map part of the event-domain, the error almost doubles to 0.266 m. However, in some experiments, outliers occurred, leading to errors of multiple meters. Typical causes were outlier measurements, caused by abrupt motions at holds, exceeding the sensor's range and thereby affecting the transition estimator, as well as grips to the wall near a hold, causing the particle filter to shift the overall estimate towards the hold. In such situations, the approach might lose track of the sensor and generate huge estimation errors.

Discussion

Overall, we demonstrated that it is possible to conduct position estimation of a climber's hand in a bouldering scenario by using an inertial sensor only. The median error that was achieved in our experiments is significantly below the distance between two holds on a typical bouldering route, making an actual application appear realistic. However, of course, routes still exist that do not meet this condition. Furthermore, it is shown that the incorporation of event-domain knowledge leads to a significant decrease of the error. In comparison to existing approaches for route classification, our approach provides position information for any point of time of the activity, enabling a later analysis of the climber's motion, if desired. Nevertheless, the described outlier cases still require solutions such as sensors with a wider measurement range or a model that differentiates more reliably between gripping a wall or a hold. Using IMUs for this kind of sports application bears several advantages over other sensors such as cameras, for instance lower costs, less space and time for setup, and no problems regarding occlusions. In addition to the proof of concept of inertial sensor-only position estimation in bouldering, our work results in a rich dataset that is available as Open Source and provides other researchers opportunities for their work. The presented results are based on an offline approach that incorporates computationally expensive approaches. For an online application on a wearable device, one has to consider some adaptions. The results indicate that replacing the particle smoother by a standard particle filter, which can be assumed to run in realtime on a wearable device, only leads to a small loss in precision. Furthermore, the least squares approach in the transition estimation also needs to be replaced, for instance by a Kalman filter. However, a comparison of precision regarding this component remains future work.

Conflict of interest We declare no conflicts of interest.

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