Gait Analysis on the move: The Infinite Gait Walkway

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Keywords: Gait analysis, smart walker, assistive robotics.

Abstract

In order to analyze human gait patterns, highly accurate data must be collected at high frame rates. The state of the art is to deploy a carpet-like structure instrumented with pressure sensors, which allows for measuring position, orientation and pressure of each foot at each step.

Since such gait "walkway carpets" are highly expensive[1] and also limited in length, we propose an alternative in the form of a wheeled walker equipped with a consumer depth camera. We have designed and implemented algorithms that derive the same set of parameters from the depth data as in a gait walkway system, however without the need for the physical presence of a walkway carpet. Moreover, we are able to provide additional information, due to continuous observation of the gait cycle, i.e. not only when the user steps on the ground. In order to retrieve actual foot pressure information, we use a shoe insole sensor.

Our experiments show that the system is able to collect gait relevant data with sufficient accuracy and frame rates. While the feet's position accuracy depends primarily on the noise of the depth sensor and is typically at a precision of less than 3 mm, the orientation accuracy is around 1-2 degrees for typical foot orientations.

1 Introduction

Gait analysis is the systematic study of human walking using the eye and brain of experienced observers, augmented by instrumentation for measuring body movements, body mechanics and the activity of the muscles [1]. Changes in gait reveal key information of special interest to tracking the evolution of different diseases: (a) neurological diseases such as multiple sclerosis or Parkinson's; (b) systemic diseases such as cardiopathies (in which gait is clearly affected); (c) alterations in deambulation dynamics due to sequelae from stroke and (d) diseases caused by ageing, which affect a large percentage of the population [3]. Accurate and reliable knowledge of gait characteristics at a given time, and even more importantly, monitoring and evaluating them over time, enable early diagnosis of diseases and their complications and help to find the best treatment. Continuous gait analysis can also assess the risk of falling, e.g. stride-to-stride variability has been shown to be an effective predictor of falls [2].

The traditional scales used to analyse gait parameters in clinical conditions are semi-subjective, carried out by specialists who observe the quality of a patient's gait while the patient walks. This is sometimes followed by a survey in which the patient is asked to give a subjective evaluation of the quality of their gait. A disadvantage of these methods is that they give subjective measurements, particularly concerning accuracy and precision, which in turn have a negative effect on diagnosis, follow-up and treatment. Progress in new technologies has given rise to devices and techniques that allow for objective evaluation of various gait parameters, resulting in more efficient measurement and providing specialists with a large amount of reliable information on patients' gaits. This reduces the margin of error caused by subjective techniques. Two such measurement tools commonly used in clinical gait evaluation are force platforms or gait walkways, the latter being a carpet like structure instrumented with pressure sensitive elements (sensels). One system that is now in common use is the 'GAITRite®' [8][9]. Recent advances in robotics make it possible to turn a standard assistance device, such as a walker, into an augmented device. Thus existing single shot tests can be enriched by a new set of continuously measured criteria derived from the daily use of standard assistance devices [2].

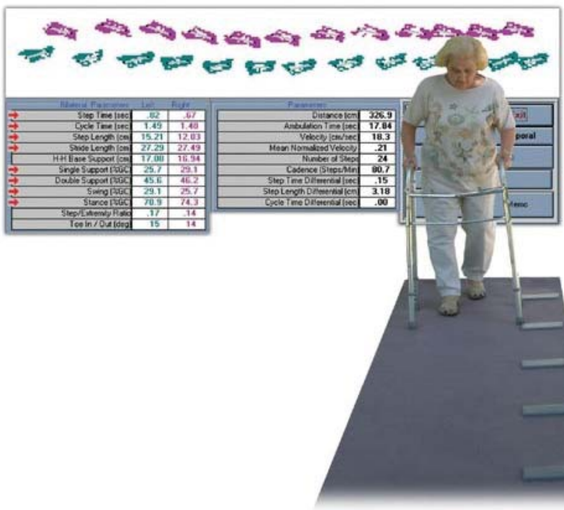

Figure 1: GAITRite® instrumented walkway system.

In this paper we propose a system that tracks specific parameters for biomechanical gait analysis. The system consists of a four-wheeled walker ("rollator") mounted with

[1] According to a desk search on various vendors between 25k€-50k€.

depth-sensors and odometers. In our work the focus is set on clinical applications and active living. Actually these two are brought together forming a continuum of data acquisition and analytics. The clinical application profits from measurements in daily life scenarios, which is likely to reduce the bias introduced in the clinical environment and vastly increases the amount of accessible data.

The main contribution of our work is the spectrum of information we derive and the "virtual" walking carpet data representation without the need for a gait walkway to be physically present. Additionally, we provide a real-time implementation (15-30 fps) that allows us to support very time-constrained algorithms.

2 Related Work

Since its beginnings in the 19th century, research on gait analysis has centred on achieving quantitative objective measurement of the different parameters that characterize gait in order to apply them to various fields such as sports, identification of people for security purposes, and medicine [3]. In our work the focus is set on clinical applications and active living. Clinical evaluation of frailty in the elderly is the first step to assess the degree of assistance they require. A comprehensive overview of the diversity and plurality of sensing modalities in the context of clinical applications is given in [3]. Reference [2] specifically raises the question if smart walkers can be used for gait monitoring and fall prevention. It considers several available smart walker implementations and concludes that standard biomechanical features such as walking speed, cadence and step length can be estimated from observing rollator walking while "*...some other information seems hard to obtained without equipping the user (3D feet positions, force pressure distribution on the ground)*". We are particularly aiming for this type of information in our work.

More specific references on individual systems in the context of an instrumented smart walker relying on a depth sensing device (e.g. Microsoft® Kinect™ sensor) are given in [4,5,6,7]. These systems do either clearly exceed our real-time runtime constraint [5,6] or do not explicitly report on the runtime behaviour, which has been a major constraint in the development of our system.

3 Parameters we aim to measure

We aim to generate all key data generated by a physical gait walkway instrumented with pressure sensels as illustrated in Figure 1, i.e. the exact placement of the feet on the ground including their orientation and the pressure force applied to the ground on foot touch. The latter actually changes over time from an initial foot contact towards the "toe-off" phase. From a representation like this a multitude of higher-level semantic information can be derived, e.g. the step and stride length, step width and the cadence. However the focus of this paper is set on generating the basic information since the derivation of the higher-level information is in most cases straightforward assuming a sufficiently precise measurement of lower-level information.

In contrast to a physical gait walkway we can also track the feet and associated key points on the feet (like the tips of the feet) continuously during the whole gait cycle, i.e. including the swing phase. This allows for e.g. temporal representations of the foot height.

Since we are by no means restricted to a straight walkway due to our Ackermann steering geometry in a front wheel steered walker we need to derive a strategy on how to visualize arbitrarily shaped – and possibly very long – walker trajectories. We opted for the following strategy:

- The chosen visualization consists in a non-length restricted but straight gait walkway. Since we observe the motion pattern of the feet from the fixed perspective of the depth camera on the walker, the walkway gets linearized implicitly. This strategy is driven by the rationale that in gait analysis as opposed to odometry, the absolute path taken is less relevant but the focus in on the relative and hence local motion pattern.
- However, an increasingly tight curve radius will affect the pattern of the feet movements. More precisely, this effect will gain the higher the change in orientation in the walker is between two subsequent steps. Instead of aiming to compensate the different curve radii of the inner and outer foot we decided just to mark the increment in the walker orientation between subsequent foot placements, which allows for information filtering in subsequent processing.

4 Our instrumented wheeled walker

Figure 2 shows the approximate depth sensor position on the walker and indicates its field of view. While this sensor is mounted on the walker, the insole sensors are worn by the user. In this work we rely on a pair of wireless "Moticon OpenGo" [10] sensor insoles, as also shown in Figure 2.

Figure 2: Instrumentation of our wheeled walker (left), utilized wireless insole "*Moticon OpenGo*" sensor (right)

Foot pressure information is mainly deemed to be relevant in clinical gait analysis while for continuous everyday inspection of gait symmetry and confidence a light-weight system without the insole sensor might also be considered a viable option, eliminating the need to instrument the user's shoes. However, the insole sensor is mandatory in order to cover the full spectrum of data of a physical gait walkway.

5 Algorithms for parameter retrieval

The algorithms designed for deriving the desired parameters solely rely on the sensor's depth data, which is represented as a depth map. An equivalent representation as a 3D point cloud can be obtained by applying

$$x = [(u - c_x)\, d] / f_x$$
$$y = [(v - c_y)\, d] / f_y$$
$$z = d,$$

where d is the depth value at pixel (u,v), f_x and f_y the sensor's focal length in pixels in x- and y direction, and (c_x, c_y) the principal point.

5.1 Ground Plane Estimation and Point Cloud Filtering

In order to allow for height estimation, the ground must be identified to provide a basis. We assume the area around the walker to be planar and apply a RANSAC-based [11] plane fitting approach to compute the plane parameters. The inlier threshold used in the RANSAC core is set to a value in the proximity of the standard deviation of the sensor noise.

Figure 3 shows the initial sensor coordinate system [x', y', z'] and the resulting ground plane coordinate system [x, y, z]. All 3D points are transformed to the plane coordinate system.

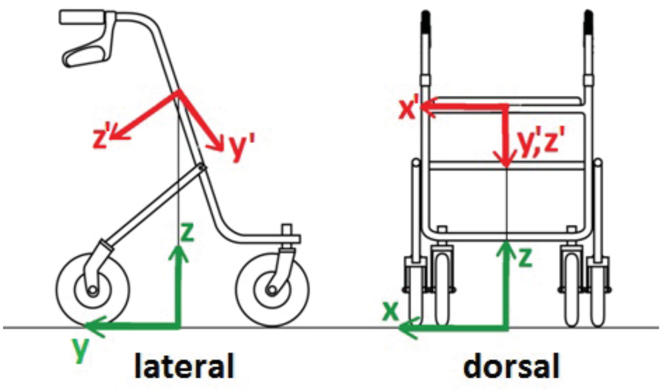

Figure 3: Sensor and Walker Coordinate System

Depending on the sensor placement, mechanical parts of the walker (e.g. the wheels) are visible in the depth map and are masked out. Since one does typically not lift a foot higher than a few centimetres during a step, 3D points located higher than 15 cm above the ground plane are also removed. Only the remaining points are used for the subsequent detection algorithms.

5.2 Foot Cluster Detection

The first step in determining the exact position and orientation of each foot is to identify the two respective clusters in the point cloud. This can be complicated by the presence of other objects on the ground that the user passes.

We use the fact that during walking, the feet are mainly oriented towards the walker and therefore visible as clusters elongated in the y-direction. All points are projected onto the ground plane, which is divided into strips in y-direction, as shown in Figure 4. In each strip, clusters in x-direction are searched (small yellow dots in Figure 4). Only points without a neighbouring, further toward the front lying point with similar x-value (~ 5 cm distance) are retained, yielding only the foremost points of each cluster (larger, green dots in Figure 4). Using this procedure, we are able to successfully identify both foot tips, even whether the feet touch (since they usually never touch at the very front).

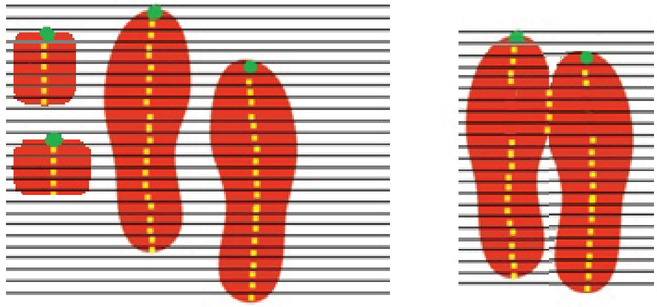

Figure 4: Foot Cluster Detection. Left: Other objects complicate the detection process. Right: Feet touch, but tips can still be identified.

In case there are more than two potential foot tips, we identify the correct ones by computing a score for each cluster and selecting the ones with the highest values.

First, all points that are within ~30 cm from the tip's y-value and differ not more than ~7 cm in x-direction are selected. The score is then computed as

$$S = N_{back} - \alpha\, N_{front},$$

where N_{back} is the number of points lying behind the tip (higher y-value), N_{front} the number of points in front and α a weight factor (set to 2 in our experiments). The score is high for foot-shaped clusters and low for small clusters, clusters that lie behind others or that are only large in x-direction.
If the scoring does not yield a clear result, we also use the position of the feet in the previous frame – if available – for correct assignment, by choosing the closest one.

5.3 Cluster Refinement

The two resulting initial foot positions indicate a rough location of the user's left and right foot tip. It is necessary to determine all corresponding 3D points for each foot, in order to enable estimation of the exact position and orientation. Especially if the feet touch (cf. Figure 4, right) this is not a trivial task. The algorithm we designed to solve this problem works as follows:

1.) Create a binary image showing all pixels in the depth map that correspond to the relevant 3D points. Find connected components and check if the initial foot positions are located in different ones. If they are, all points within the tip's component are selected for that foot.

2.) If the initial positions are within the same component, check if the feet can be separated in 3D space by performing a flood fill on the relevant part of the depth map.

3.) In case the feet are not separable using the above procedures, we seek the "best" cut through the connected region. We solve this problem directly in the depth map by defining a graph, were the cost of a connection to the neighbouring pixels is the negative depth value at these pixels. Therefore, we aim for the path with the lowest accumulated height values, which is most likely the correct cut due to the shape of the feet. The starting point for the cut is the foremost position where the feet touch. In order to make the algorithm more robust, we accumulate the depth values of several pixels in each direction before deciding which direction to move to.

Figure 5 illustrates how each of these steps can assign the corresponding points for each cluster in certain scenarios. Step 1 is successful if the data can be separated in 2D, i.e. its projection onto the ground plane. Step 2 is computationally more expensive and can perform the cluster assignment if the feet are separable in 3D space. In case the feet touch, Step 3 must be applied, which computes the ideal cut through the adjacent clusters.

Figure 5: Left: Step 1, Middle: Step 2, Right: Step 3

The advantage of this 3-step procedure is that in a typical gate cycle, in the vast majority of frames the feet can easily be separated in 2D, and the computationally more expensive subsequent steps need to be performed only when necessary. This increases the average frame rate compared to using only a single, albeit more sophisticated algorithm.

5.4 Foot Position and Orientation

In order to estimate the orientation, we perform a Principal Component Analysis on the cluster points of each foot. The direction is then set to the Eigenvector corresponding to the largest Eigenvalue of the covariance matrix.

We then project each point onto the direction vector and select the foremost point in this direction. This point, together with the direction vector and the user's foot length, unambiguously defines the foot's position.

5.5 Walker Ego-Motion

Since the coordinate system moves with the walker, it is necessary to compensate for the walker motion. The origin of the coordinate system stays at the projection of the camera centre to the ground. While the walker moves, any position recorded in the past must be moved in the opposite direction by distance the walker travelled.

One option is to use wheel odometry or inertial sensors to recover the ego-motion. In order to avoid additional hardware requirements, we implemented a vision-based method.

At each step cycle, there exists a point where both feet touch the ground. At this moment, we record the feet positions. Until this point occurs again, the walker's ego-motion can be determined by computing distance in y-Direction between the foot standing still and the stored position.

6 Experimental results

Typical output produced by our system is shown in Figures 6 and 7. Figure 6 shows that the same data is generated as in the physical gait walkway in Figure 1, i.e. the feet's position, orientation and pressure distribution at each step. While the figure only shows a short sequence, every step the user takes is visualized and the data is stored to disk for further analysis.

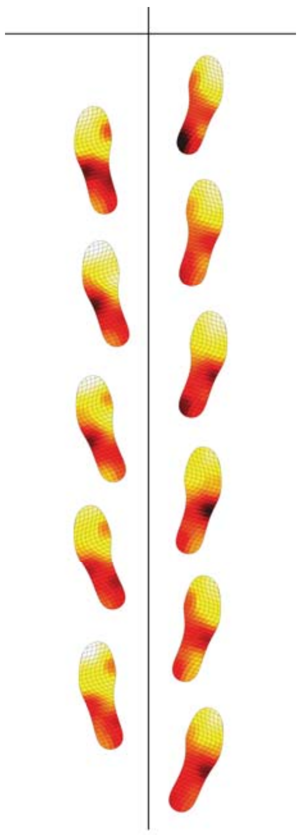

Figure 6: "Virtual Walkway" result sample.

Figure 7 shows a sample trajectory of the foot tips. It illustrates how our system is not only capable of generating data at each step on the ground, but also during the swing phase.

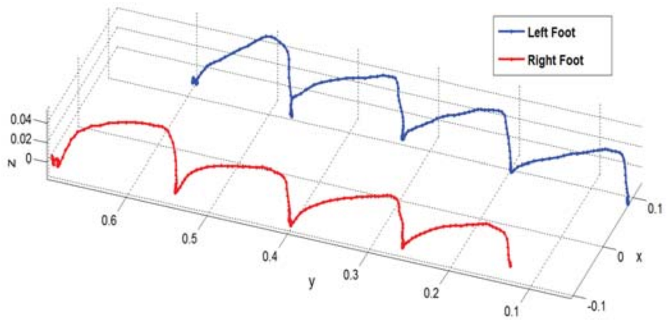

Figure 7: Sample Trajectory of the Foot Tips

The algorithms in Section 5 are designed with a strong focus on speed, which makes it possible to achieve the desired frame rate of 15-20 Hz on a single Intel®-i7 CPU core using a depth map resolution of 640x480 pixels. If higher frame rates are required, the depth map can be sub sampled to around a quarter of the resolution without influencing the results, making frame rates at around 30 Hz possible.

In order to estimate the accuracy of both position and orientation, we performed an extensive evaluation using the Microsoft® Kinect™ sensor.

For ground truth generation, we printed several identical feet patterns and placed them at different positions and angles behind the walker. Since absolute trajectories and positions are not relevant for gait analysis, but only the accuracy at each single step matters, we measure relative angles between the patterns and the distances between the foot tips.

As shown in Table 1, the average position accuracy turned out to be slightly less than 3 mm, evaluated in 20 measurements. The error is independent of the step length. Part of the deviation can be explained by the average 3D point resolution of ~1.5 mm and minor inaccuracies at ground truth capturing. Table 2 shows the results of the angle accuracy evaluation. The error increases with the angle, mainly due to occlusions. However, at typical angles when walking (0-15°) the average error of 1.6° is only slightly higher than the ground truth accuracy.

N	μ_{error}	Med_{error}	σ_{error}
20	2,96 mm	2,93 mm	1,68 mm

Table 1: Position Accuracy

Angle	N	μ_{error}	Med_{error}	σ_{error}
0°–15°	40	1,62°	1,39°	1,17°
15°-30°	40	2,26°	1,86°	2.05°
30°-45°	40	3,16°	2,86°	2,18°

Table 2: Angle Accuracy

For comparison, we have evaluated the accuracy of an inertial measurement unit (IMU), namely the *Inertial Elements Osmium MIMU22BT* [12]. Osmium produces MIMUs (*multi IMU*) that operate by fusing the measurements of several low cost sensors resulting in enhanced measurement performance. The Osmium MIMU22BT is closely related to the *OpenShoe* project, an open source foot-mounted inertial navigation system (INS) [13] initiative. We used *OpenShoe* scripts for data acquisition. While manual calibration can be performed for each individual device using a special calibration object, we used the manufacturer default calibration for practical considerations regarding a potential later deployment, i.e. for being applicable for our target group simplicity in deployment is a factor of high importance.

As shown in Figure 7, the IMU has been attached to the tip of the foot. Table 3 shows the evaluation results. Compared to our results, it turns out that the angles can be measured more accurately using the IMU, but the position error is significantly higher.

Figure 8: IMU attached to the tip of the foot.

$\mu_{Position}$	$Med_{Position}$	$\sigma_{Position}$	μ_{Angle}	Med_{Angle}	σ_{Angle}
7,3 mm	6,0 mm	6,6 mm	0,65°	0,50°	0,50°

Table 3: IMU Evaluation Results

7 Conclusion & Outlook

By upgrading a standard wheeled walker with a depth sensor (e.g. Microsoft® Kinect™), we are able to cover the same position- and orientation measurements as a deployed gait walkway instrumented with pressure sensors, which is currently the state of the art in gait analysis. In addition, we are able to produce continuous measurements during the whole gait cycle, i.e. including the swing phase. This is achieved at rates of 15-30 Hz (depending on the hardware and resolution), which allows for real-time gait pattern analysis.

While the feet's position and orientation are obtained with sufficient accuracy using the depth sensor, foot pressure measurements demand additional hardware in form of a commercialized insole sensor. Nevertheless, such a sensor is still an order of magnitude cheaper than a fully instrumented walkway system.

Depending on the user's gait pattern, occlusions can affect the system's ability to capture the feet positions. In our future work, we intend to investigate to what extent mounting a second depth sensor yielding an additional viewpoint can overcome these problems. Recent innovations in 3D depth sensing (e.g. Intel® RealSense™ R200/F200, PMD® CamBoard pico flexx) will be considered and support our aims twofold: First, the form factor/power consumption will allow for a seamless integration into the walking frame. Second, we expect that some combination of sensing devices is likely to support our aim for outdoor/sunlight compatibility as required for continuous measurements in daily activities.

Furthermore our future work will address the measurement of additional data relevant to gait analysis, e.g. position of the knees in 3D space and the angles between the lower leg and the upper leg, and the lower leg and the foot, respectively. That way we want to produce a skeletal animation of the limb movement during motion, as well as derive higher level semantic information like the joint angle and angular velocity plots discussed in [1].

Acknowledgements

The research leading to these results has received funding from the European Union's Horizon 2020 research and innovation programme under Grant agreement n. 643644 ("ACANTO – A CyberphysicAl social NeTwOrk using robot friends"). For further information about the project see http://www.ict-acanto.eu/ .

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