Validation of a Motion Capture Suit for Clinical Gait Analysis

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ABSTRACT
Gait analysis is often supported by technology. Due to limitations in optical systems, such as limited measurement volumes and the requirement of a laboratory environment, low-cost inertial measurement unit (IMU) based motion capture systems might be better suited for gait analysis since they involve no spatial limitations and are flexibly applicable.
In this paper, we investigate if low-cost IMU-based motion capture suits are an adequate alternative for clinical gait analysis in terms of accuracy of the determination of joint flexions and gait parameters. For this reason, we developed a gait analysis system and a gait analysis algorithm, which detects joint positions based on the Joint Coordinate System and determines knee, hip, and ankle flexions, as well as spatiotemporal parameters such as the number of steps, cadence, step duration and step length, and the specific gait phases.
We evaluated and validated the IMU-based system in comparison to camera-based measurements (as gold standard) with three different healthy adult subjects. The evaluation indicates that the full-body motion capture system achieves a high degree of precision (0.86) and recall (0.98) in the recognition of gait cycles. The harmonic mean $F_{0.15}$ of the two factors precision and recall is on average 0.96 and the mentioned temporal gait parameters can be determined with an error below 10 ms. The mean deviation in the determination of joint angles amounts $1.35° \pm 2°$. Consequently, the article at hand indicates that low-cost IMU-based motion capture suits are an accurate alternative for gait analysis.

Author Keywords
gait analysis; IMU; motion capture; validation; low-cost; Joint Coordinate System; joint angles

ACM Classification Keywords
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INTRODUCTION
Gait analysis is often helpful in the medical management of those diseases which affect the locomotor system [10]. Thereby, the basic gait parameters are gait speed, step length, step frequency, and joint angles [12]. The traditional scales, which are used to analyze gait parameters in clinical conditions, are semi-subjective, carried out by specialists who observe the quality of a patient's gait by making him/her walk [11]. But since the human gait is a complex process, subjective observations are often insufficient. According to Bachmann et al. [2], it is not possible to identify and to memorize all aspects of the gait at the same time in 3D without technical resources. Furthermore, some aspects like ground reaction forces are inaccessible via visual observations. However, these deficits can be compensated by technology-supported gait analyses, which allow objective evaluations and make measurements more efficient and effective [11].
In accordance to Muro-de-la-Herran et al. [11], existing techniques for gait analysis can be divided into three categories: those based on image processing (IP), on floor sensors (FL) and wearable sensors (WS). The typical image processing systems consist of several cameras. Whereby, image-based methods can be marker-less or employ active or passive markers [4]. Nowadays optical motion capture (mocap) measurement systems like VICON are often considered as "golden standard", because these systems provide accurate position information (errors in the range of up to 1 mm precision) [14] if calibrated properly. However, optical systems entail also some disadvantages. The most important factors are their high costs, a limited measurement volume, the limitation to apply them inside a laboratory environment and they typically require (manual) post-processing to achieve accurate results. While requiring no manual post-processing and achieving a high accuracy out of the box, floor sensors, are as well mainly applicable to laboratory settings, due to their high price and their limited sizes (of typically a few meters length).
Because of these limitations, the IP and FL systems are rarely applied to clinical assessments. The advantages of inertial motion capture systems lie in no spatial limitations. Outdoor measurements are possible as well as large area measurements in any lighting. Further advantages are their flexible and easy applicability.
Among the available reporting standards of the International Society of Biomechanics (ISB) for the human gait, the determination of joint flexions and rotations is most applicable, since it applies optimal to the clinicians' conceptual view when using individual axes embedded in the proximal and distal segments. Thus, this encoding supports an optimal inclusion of calculations for clinically relevant joint translations [18, 19].
To our knowledge, there is a lack of using low-cost inertial

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full-body sensor suits for clinical gait analysis. Especially, the reporting standards and therefore, the medical and physiological knowledge about the human gait is not optimally utilized in many studies.
Consequently, we propose a gait analysis system and implement algorithms for the determination of joint flexions and gait parameters based on the measured data. Furthermore, we investigate the resulting system's suitability as an alternative reference system for clinical gait analysis by evaluating it in comparison to camera-based measurements in terms of accuracy of the joint flexions and the spatiotemporal parameters as well as precision and recall of the step recognition.

RELATED WORK

Due to the high importance of gait analysis, several approaches of technology-supported gait analysis and ambulatory gait analysis methods using wearable technology have been proposed, as summarized by Tao et al. [17].
An overview of studies of algorithms to detect human lower limb biomechanics using IMUs can be found in [6]. Besides walking, other motions related to the lower limbs like stair climbing or sit-to-stand movements are considered as well in this review.
Among existing works, Lee et al. [10] used a prototypical low-body motion capture system with four IMUs, attached to patients' upper and lower legs, for the investigation of spatiotemporal parameters. Their results are compared with the optical VICON system. The system estimated the stride length (of 30 steps) with an average error of 2.3% in the experiments. But the system does not convert movements of the inertial sensors into joint positions and therefore, the knowledge about the clinical gait analysis is not optimally utilized in this work.
The Xsens inertial motion capture suit, which consists of 17 inertial and magnetic sensor modules is mentioned in [15]. Pons-Moll et al. [13] uses orientation data obtained from a small set of inertial sensors attached to the outer extremities (five sensors at the positions: neck, wrists, and ankles) to stabilize a markerless motion tracking approach.
Seel et al. presented in [16] an IMU-based (Xsens MTw) joint angles measurement for gait analysis. The sensor positions are upper and lower leg, as well as the foot on each side. The results are compared to an optical 3D motion capture system. The root mean square (RMS) errors of the knee flexion/extension angles found to be less than 1° for knee flexion on a prosthesis and 3° for the human leg. The RMS error for the flexion of the ankles is about 1°. Hip flexion/extension are not taken into account as well as the determination of gait parameters.
While this selection shows that there are some good approaches in using IMUs for gait analysis, it indicates a lack of using inertial motion capture suits in combination with expert knowledge to offer the measured data in a bio-mechanically interpretable way.

GAIT ANALYSIS FRAMEWORK

As shown in the previous section, there is still a lack of systems that encode the gait information recorded via IMU-based motion capture suits in a bio-mechanically interpretable way. Therefore, we developed a system for joint-based gait analysis that collects gait movements via IMU-based full-body motion capture suits, interprets them regarding joint-based movements and thus, supports an adequate gait analysis algorithm. Within the design of the system, we considered its general applicability for various sensor systems and analysis algorithms as essential to assure their broad usability.
Since the systems architecture uses a modular approach with defined interfaces among each component, various components can be exchanged in order to support specific use cases. Figure 1 shows a simplified view of the resulting framework architecture, and the system components, which are described in greater detail in the following subsections. The framework architecture itself (big green colored box in Figure 1), checks the compatibility of the components, wires the components at run time, executes the workflow and enables repeated analysis with different analysis strategies (e.g. by altering algorithms' parameter settings).

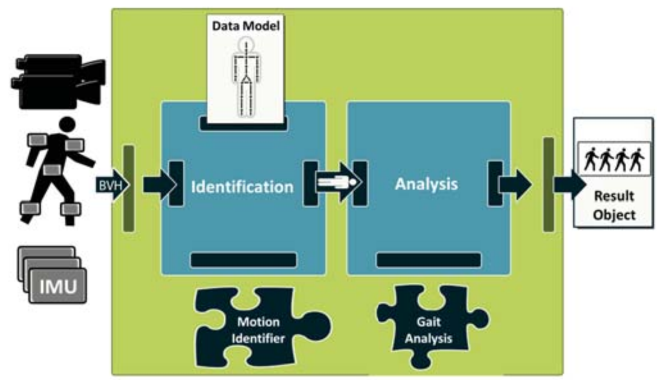

Figure 1. A simplified view of the resulting framework architecture, and the system components: Framework (green), Component (blue), OO-Data model (white), Data flow (arrow), Interface (slots), Interface realization (puzzle).

Data Model

Considering medical expert knowledge, movements of the inertial sensors are converted into joint positions according to the Joint Coordinate System (JCS) in order to get bio-mechanically interpretable values. On the basis of the joint positions, knee, hip, and ankle flexions can be determined as well as gait phases and spatiotemporal parameters such as the number of steps, cadence, step duration and step length. The data model (white box in Figure 1) defines an object-oriented data structure for the motion data according to the recommendation of the International Society of Biomechanics (ISB) [19]. The model realizes the access to the data of body sections such as joints and realizes data related operations. Furthermore, the model allows the extension of further data sources such as electromyography measurements. Figure 2 shows the data structure of the data model, which defines an object-oriented data structure for the motion data according to the recommendation of the International Society of Biomechanics (ISB).

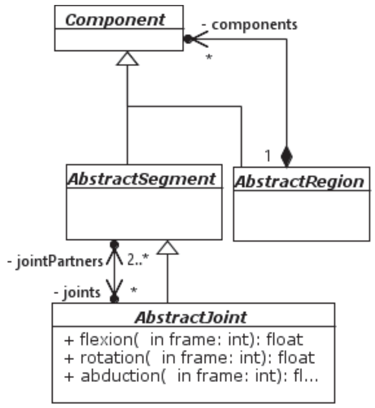

Figure 2. Data structure of the data model, which defines an object-oriented data structure for the motion data according to the recommendation of the International Society of Biomechanics.

System Components

The system components, illustrated in Figure 1 (blue), are divided in the tasks identification and analysis, which are described in the following.

Identification

The identification component reads the raw data streams and converts them into the structure of the defined data model. Whereby, the identification algorithm might vary depending on the data source. The component returns the data object.

Analysis

The analysis component uses the data object for motion analysis and executes the analysis strategy. In this article, we implemented a gait analysis strategy. But the analysis of other activities or motions like climbing stairs or getting up from a chair can be extended in further work. This component executes the analysis algorithms and returns the result object and encodes detected activities or gait parameters as described in the following subsection.

Result Object

The result object (right side in Figure 1) defines the operations on the data related to the result. In the analyzed use case of step-detection for gait analysis, the result object defines the operations for the calculation of spatiotemporal parameters and consequently includes the cadence, velocity, stride length, and the duration of the specific gait-phases. Figure 3 shows the data structure of the result object.

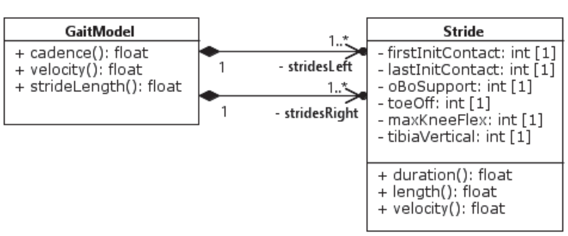

Figure 3. Data structure of the result object. The result object defines the operations for the calculation of spatiotemporal parameters like the cadence, velocity, stride length, and the duration of the specific gait-phases.

Supported File Formats

Motion capture systems typically support the export of the measured data to several standard file formats like FBX, C3D, BVH, and CSV. Therefore, our system enables the reading of the BVH format. The raw data is transferred into an object-oriented data structure in order to offer an easier handling and data structuring.
In this work, we use the BVH (Biovision Hierarchical Data) file format, which is able to constitute all bones of the human body and other segments.

GAIT ANALYSIS ALGORITHM FOR A FULL-BODY MOTION CAPTURE SYSTEM

The developed gait analysis algorithm applies the following basic movement characteristics of a gait. The definition of a gait cycle is related to a reference leg and takes from the initial floor contact at the beginning of a step till the initial contact of the same leg at the next step. The gait cycle (illustrated

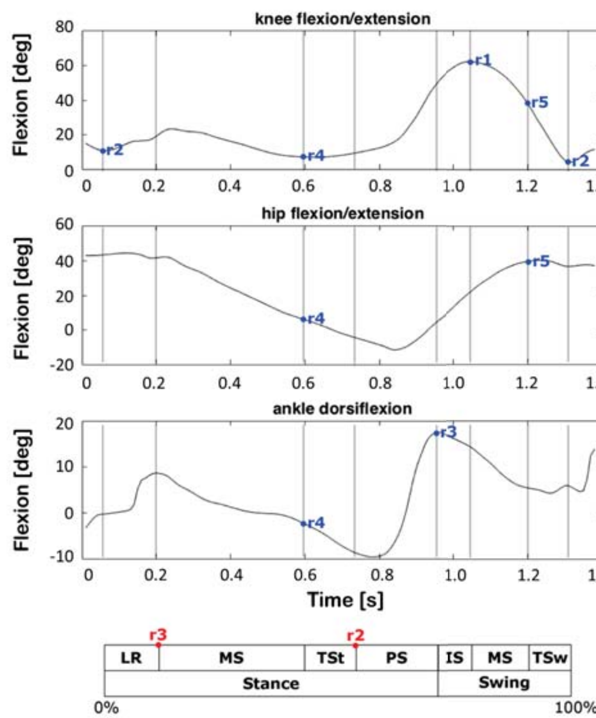

Figure 4. Gait analysis based on the rules (r1)- (r5). All rules (except rule (r4)) are based on finding distinctive points in the gait cycle. Blue rules are based on the reference leg; red rules take the contralateral leg into account. The distinctive points are: (r1) - maximum knee flexion, (r2) - initial contact with the heel strike, (r3) - the toe off, (r4) - heel off, and (r5) - vertical tibia position. The bar below shows the gait cycle with the phases loading response (LR), mid-stance (MS), terminal stance (TSt), pre-swing (PS), initial swing (IS), mid-swing (MS), terminal swing (TSw).

in Figure 4) is divided into several super- and subordinated phases. The superordinated phases are the stance phase and the swing phase, which are determined for each leg. Within these phases, there are the subordinated phases. The stance phase begins with the initial contact and the heel strike, over the foot flat and the loading response (LR) to the midstance phase (MS), where the body is supported by one single leg.

The stance phase ends with a heel off in the terminal stance (TSt) and the swing phase (SW) starts. The swing phase is separated in the pre-swing (PS), the initial swing (IS), the mid-swing (MS), and the terminal swing (TSw) phase. Theses phases are characterized by a toe off, the mid-swing and a heel strike.
In the swing phase, two extra phases of acceleration and deceleration can be recognized. The acceleration phase goes from toe-off to mid-swing, while deceleration goes from mid-swing to heel strike. Between these two phases, the mid-swing phase occurs [3]. Figure 4 also shows the knee, the hip, and the ankle flexion during a gait cycle.
On the basis of the joint positions of the knee, the hip, and the ankle the mentioned phases can be clearly distinguished. Therefore, our algorithm for the recognition of the specific gait phases is based on joint positions. The joint positions and velocities for distinctive points, in accordance with [8], are listed in Table 1.

Table 1. Joint positions and directions of velocities for distinctive points in the gait cycle. The directions are marked by arrows, whereby an up arrow stands for an increasing flexion, the down arrow for a decreasing flexion and the line for a neutral position.

Position	hip flex.	knee flex.	ankle flex.
initial contact	$20°, \downarrow$	$5°$, -	$0° \uparrow$
mid stance	$0°, \downarrow$	$5°, \uparrow$	$5° \downarrow$
initial swing	$15°, \uparrow$	$60°, \uparrow$	$-5°$ -
max. knee flex.	$15°, \uparrow$	$60 - 80°$, -	$-5° \uparrow$
mid-swing	$25°, \uparrow$	$25°, \downarrow$	$0° \uparrow$

Consequently, our algorithm is based on the following 5 rules:

(r_1) The *maximum knee flexion* is the most significant event in a gait cycle and can be easily recognized. This rule is searching for a maximum with a joint angle between $45°$ and $60°$.

(r_2) The *initial contact* with the heel strike characterizes the beginning and the end of a stride. Thus, they are very important to recognize a stride. At this point, there is a lowest knee flexion in the range of $-5°$ to $15°$. These points are only identified in our algorithm if the maximum knee flexion was detected in the step before.

(r_3) The *toe off* is a maximum in the motion data of the ankle dorsiflexion. The rules (r_3) to (r_5) will be only searched, if a stride could be clearly recognized based on the rules (r_1) and (r_2).

(r_4) The *heel off* is characterized by a neutral joint position of the knee, hip, and ankle, viewed from the sagittal plane. Finding this event is difficult because there are no extreme points. Due to this fact, all three joints are used for recognition.

(r_5) The *vertical tibia position* is characterized by the same angular position of the knee and hip joint of about $20°$ to $35°$. Additionally, the angular velocity and acceleration of the knee must be significantly reduced during this event.

Figure 4 demonstrates the rules r_1 - r_5. All rules (except rule r_4) are based on finding distinctive points in the gait cycle. These distinctive points are significant events, which separate the phases in a gait cycle. Because the joint positions vary, the joint velocity and joint acceleration are decisive for our algorithm instead of the angles. A stride is recognized, if the maximum knee flexion r_1 and the initial contacts r_2 are found.

APPLIED FULL-BODY MOTION CAPTURE SYSTEM

While the system is generally applicable to various inertial motion capture suits, we used a low-cost full-body motion capture system of Motion Shadow [1], which includes 17 motion nodes for evaluation purposes. Figure 5 shows the human joints (black dots) and the positions of each motion node (red boxes) of the suit. A motion node is a 9-DOF (degree of freedom) inertial measurement unit and has a physical size of $35 \times 35 \times 15\,mm$ and a weight of $0.01\,kg$. The sampling rate of each sensor is $100\,Hz$. The included accelerometer measures the linear acceleration in g, whereby $g \approx 9.81\,ms^{-2}$, with a resolution of $190\,\mu g \pm 5\%$ at $2\,g$ range. The range or sensitivity is $\pm 2\,g$ or $\pm 6\,g$ depending on the configuration and the noise density is about $50\,\mu g/\sqrt{Hz}$. The included gyroscope measures the angular velocity in $° \cdot s^{-1}$ with a resolution of $0.07° \cdot s^{-1}$. The range or sensitivity is $\pm 2000° \cdot s^{-1}$ and the noise density is about $0.1° \cdot s^{-1}$. The third included sensor is the magnetometer, which measures the magnetic field strength in T with a resolution of $0.1\,\mu T$ in a range of $\pm 100\,\mu T$. The noise density is about $0.4\,\mu T$.
Since we concentrate on a clinical gait analysis, we only use the motion nodes at the hip and the lower extremities in this work (marked with a cross in Figure 5). The sensor straps can be easily attached and removed. Due to a calibration process, there is a tolerance in the accuracy of the sensor placement.

Figure 5. Joint positions (black points) and the position of the 17 motion nodes (red boxes): Head, shoulder (left/right), breast, upper arm (left/right), forearm (left/right), hand (left/right), hip, upper leg (left/right), lower leg (left/right), foot (left/right). The marked motion nodes are used for the clinical gait analysis in this work.

ANALYSIS AND VALIDATION

We investigated the system's suitability as a reference system and an alternative to optical measurement techniques, which are often used as a gold standard in gait analysis [14]. On the basis of the recognized gait phases, the spatiotemporal parameters can be calculated.
Figure 6 shows the flexion of hip, knee, and upper ankle joint over time and the recognition of steps and the determination of the stance (blue) and swing phase (red) as well as their duration and length. On this basis, parameters such as the number of steps, cadence, step length, step duration and the duration of each gait phases can be determined. For the validation

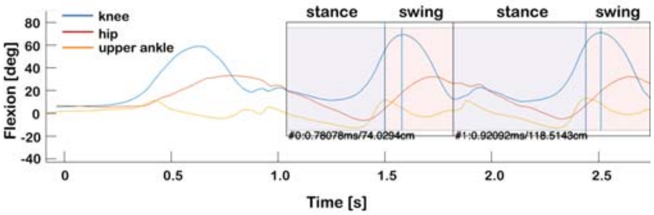

Figure 6. Hip, knee, and upper ankle flexion over time. The stance (blue) and swing (red) phases during a gait cycle are labeled in this graph. Additionally, the durations and lengths of these phases are included as well.

of the system and our gait analysis algorithm, we compared our results with an optical camera-based analysis, processed via Kinovea, a video-based motion analysis software. While Kinovea is used primarily in the sports sector, it is also a valid method for motion analysis in the field of physiotherapy [9] and thus, applicable as a gold standard. In our study, we recorded the walking data from 3 healthy adult subjects aged 22-36 years and a body height of 175-195 cm walking at normal speed, while wearing the full-body motion suit. Thereby, we analyzed 10 tests with a total number of 462 steps.

Figure 7 shows the determination of the knee flexion via Kinovea. Several lines were fixed on the floor at a distance of 50 cm to mark the total optical measurement volume of 3 m. Additionally, bright markers are taped on the hip, knee, and ankle joint positions for a better recognition of the joints in the video-based analysis. According to the medical definition of joint angles based on neutral positions, the angle of 163° corresponds to 17° (Θ_{knee}).

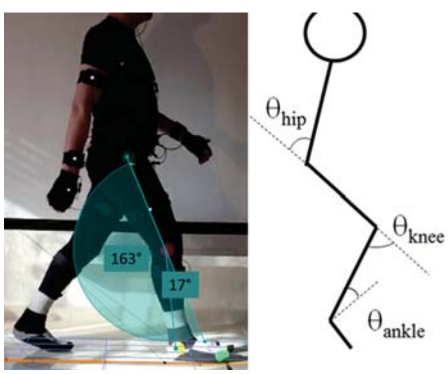

Figure 7. Determination of the knee flexion via Kinovea. According to the medical definition of joint angles based on neutral positions, the angle of $163°$ corresponds to $17°$ (Θ_{knee}).

Figure 8 shows the measured joint angles for the knee with the IMU-based full-body motion capture system in comparison to the optical camera-based system. The measured data shows the largest deviation at the minimum and maximum flexion.

Table 2 lists the angles of the maximum and minimum knee flexion measured with IMUs in comparison to the video-based measurement and their deviation. The mean deviation is about $1.35° \pm 2°$. Thereby, a total measurement error of $\pm 2°$ for the optical analysis was determined in a pre-study. This error is based on a deviation of $\pm 1°$, which results measuring the same angle several times and a further error of $\pm 1°$

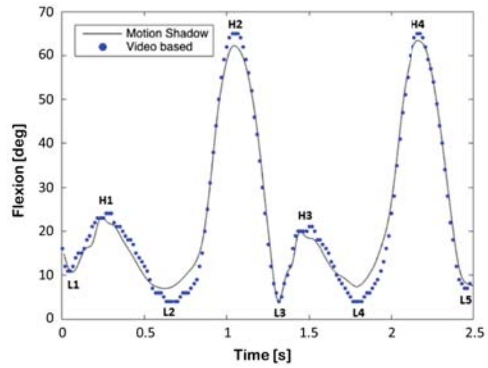

Figure 8. Comparison of knee flexion measured with the IMU-based full-body motion capture system with a camera-based system. L1, L3, and L5 are at an initial contact. H2 marks the point of the maximum knee flexion.

was estimated since Kinovea supports only integer values for the measured angles. The root mean square error (RMSE) amounts $3.5°$ (error of optical system included). The validation of the measured duration of a stride shows a mean deviation of $7\,ms$. The calculated mean deviation for the step length amounts $13.1\,cm$. The high deviation is caused by image distortion at the sides of the recording area.

Table 2. Angles of the maximum and minimum knee flexion measured with IMUs in comparison to the video-based measurement. L1, L3, and L5 are at an initial contact. H2 marks the point of the maximum knee flexion. The measurement error of $\pm 2°$ for the optical analysis is added to the deviation.

Peak	Motion Shadow	Camera based	Deviation
L1	10.68°	11°	$0.32° \pm 2°$
H1	23.3°	23°	$0.3° \pm 2°$
L2	6.97°	4°	$2.97° \pm 2°$
H2	62.22°	65°	$2.78° \pm 2°$
L3	4.11°	4°	$0.11° \pm 2°$
H3	19.93°	21°	$0.07° \pm 2°$
L4	7.34°	4°	$3.34° \pm 2°$
H4	63.41°	65°	$1.59° \pm 2°$
L5	7.65°	7°	$0.65° \pm 2°$

Finally, we investigate the recognition accuracy of the gait cycle. Therefore, recall R and precision P are calculated [5] by following equations:

$$R = \frac{TP}{TP + FN}, \tag{1}$$

$$P = \frac{TP}{TP + FP} \tag{2}$$

True positives TP are examples correctly labeled as positives. False positives FP refer to negative examples incorrectly labeled as positive. True negatives TN correspond to negatives correctly labeled as negative. Finally, false negatives FN refer to positive examples incorrectly labeled as negative. In our study we could achieve a mean precision of our algorithm of 0.86 and a mean recall of 0.98. The harmonic mean $F_{0.15}$ of the two factors precision and recall is on average 0.96 and can be calculated by equation 3:

$$F = \frac{1}{\frac{\alpha}{P} + \frac{1-\alpha}{R}}. \quad (3)$$

Our implemented algorithm should detect a broad variety of gait patterns. Therefore, the value α is set to $\alpha = 0.15$ to rate the recall higher than the precision.

DISCUSSION AND CONCLUSION

We developed a gait analysis system and showed that an inertial low-cost full-body motion capture system is suitable for a clinical gait analysis as an alternative reference system to optical systems. Therefore, we implemented algorithms for the determination of joint flexions and gait parameters under the consideration of medical expert knowledge. Finally, we evaluated and validated the IMU-based system in comparison to camera-based measurements in terms of accuracy of the joint flexions and the spatiotemporal parameters as well as the precision and recall of the step recognition.

The validation shows that our software system is able to recognize gait cycles with a high degree of precision (0.86) and recall (0.98). The harmonic mean $F_{0.15}$ of the two factors precision and recall is on average 0.96. In the review article of Muro-de-la-Herran [11] the accuracies of various systems in step recognition and gait phase detection are mentioned. FP systems achieved an accuracy of 72% (pressure sensors) to 80% (mats and platforms), IP systems show a recognition rate of 77.8% (single camera), 70.18% (Stereoscopic Vision), and 78% - 91% recognition (IR Thermography). Therefore, we could achieve a good result in step recognition in comparison to FL and IP systems.

The mean deviation in the determination of joint angles amounts $1.35° \pm 2°$ and an RMSE of $3.5°$. Seel et al. [16] listed the accuracy of different IMU-based joint angle determinations in literature. In this selection, the root mean square errors (RMSE) vary between 3° and 7°. So we also achieved good results in comparison to other systems.

Finally, we could determine spatiotemporal parameters like the number of steps, cadence, step length, step duration and the duration of stance phase and swing phase. Thereby, we could achieve errors below 10 ms for the temporal gait parameters. Despite the limited number of subjects, our algorithm detects a broad variety of gait patterns because we concentrate on the specific sequences of a gait cycle and allow a wide range of joint angles.

The use of an object-oriented data model for describing gait cycle sequences allows greater flexibility and extensibility. For example, the result model of the gait analysis can be extended by the opportunity to calculate the average step width of the subject. This information in combination with the cadence can be used to evaluate the gait regarding stability and security. A high cadence and a big step width are an indication of unsteadiness [8].

The validation shows that our system can support health professionals by providing objective measurements of gait parameters. It is not restricted to the pure gait analysis due to its extensibility. For example, the analysis of a Timed Up and Go Test [7] can be implemented as an additional analysis component regarding movements of the whole body.

However, due to the limitations in our study population, these results are preliminary. We intend to validate the system in a larger study with more subjects diverse in age and sex, as well as subjects with gait anomalies.

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