# Assessment of Gait Symmetry and Gait Normality Using Inertial Sensors: In-Lab and In-Situ Evaluation

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**Abstract.** Quantitative gait analysis is a powerful tool for the assessment of a number of physical and cognitive conditions. Unfortunately, the costs involved in providing in-lab 3D kinematic analysis to all patients is prohibitive. Inertial sensors such as accelerometers and gyroscopes may complement in-lab analysis by providing cheaper gait analysis systems that can be deployed anywhere. The present study investigates the use of inertial sensors to quantify gait symmetry and gait normality. The system was evaluated in-lab, against 3D kinematic measurements; and also in-situ, against clinical assessments of hip-replacement patients. Results show that the system not only correlates well with kinematic measurements but it also corroborates various quantitative and qualitative measures of recovery and health status of hip-replacement patients.

**Keywords:** Gait analysis, Symmetry, Normality, Accelerometer, Gyroscope, Inertial sensors.

## 1 Introduction

Quantitative gait analysis (GA) can improve the assessment of a number of physical and cognitive conditions. The importance of GA in the treatment of children with cerebral palsy is well known and documented [1]. The use of GA to monitor and assess Parkinson's Disease [2], stroke [3], and orthopedic [4] patients have also been investigated.

Despite many positive results, GA is still not routinely used in the clinical setting. Several factors contribute to the low adoption of GA as a routine clinical tool. Perhaps the most significant factor is that the accepted gold standard for GA, in-lab 3D motion capture (MOCAP), is simply not available to all patients. The costs involved in equipping a gait lab and training personnel are prohibitive for many clinical institutions, especially in underprivileged areas and developing countries.

The current alternative to MOCAP is observational gait analysis (OGA), which is intrinsically subjective and sensitive to the observer's experience [5]. Recently, however, large efforts have been employed in developing low-cost, inertial sensor systems that can complement OGA with objective and reliable information. The success of such systems will hopefully incur in a wide-spread adoption of quantitative GA as a clinical tool.

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The present study concerns the development of a inertial sensor system for GA that can be successfully deployed in the clinical setting. This system, composed of wearable inertial sensor units, can complement OGA by providing reliable quantitative measures of gait symmetry and gait normality. This study evaluates the proposed symmetry and normality measures both in-lab, against measures derived from MOCAP; and in-situ, compared to clinical assessments of hip-replacement patients.

# 2 Related Work

## 2.1 Observational Gait Analysis

Observational gait analysis (OGA) is frequently aided by video recordings, which provide certain interesting functions to the observer such as pause and slow motion. In some cases, quantitative measurements, such as joint angles, can be directly calculated from the video image [6]. This type of analysis is often accompanied by a form or questionnaire that facilitates the extraction of relevant information from the video. Two such forms have been more thoroughly investigated and more widely adopted: the Visual Gait Assessment Scale (VGAS) [7] and the Edinburgh Visual Gait Score (EVGS) [8]. Both questionnaires target the assessment of children with cerebral palsy.

OGA can be complemented by other more quantitative measurements, such as average gait speed, average step length and other gait parameters. These are typically measured during walking tests, such as the 10-m walking test [9], or the timed up and go test (TUG) [10]. The TUG is normally employed in studies where balance and risk of fall are of interest, as it requires that the subject stand up and sit down on a chair without help. The 10-m walking test is a simple way of determining, average gait speed, stride length and cadence. Average gait speed, for example, has been identified as an indicator of: activity of daily living function in geriatric patients [11]; high risk of health-related outcomes in well-functioning older people [12]; and leg strength in older people [13]. Stride length is another interesting measure that has been associated with, for example, metabolic cost and impact during walking [14].

## 2.2 MOCAP Gait Analysis

Gait may be studied in the spatio-temporal, kinetic or kinematic domains. In order to simplify the analysis of this extremely rich source of information, one may focus on measures of symmetry and normality. Symmetry refers to the similarity between the movements of the right and left sides of the body. Normality refers to the similarity between the movements of one individual compared to average movements of a population that is judged healthy or normal.

The symmetry of kinematic gait data is usually evaluated by visual inspection of superimposed curves from right and left sides. Few quantitative symmetry measures have been proposed which take into account complete joint angle curves. A measure of trend symmetry based on the variance around the $1^{st}$ principal component of a right-side vs. left-side plot has been suggested [15]. This trend symmetry measure is insensitive to scaling, and must be compensated by an additional measure, the range amplitude ratio. In contrast, the present study introduces a quantitative symmetry measure based on kinematic data which can be expressed as one index.

The Gillette Functional Assessment Questionnaire (GFAQ) Walking Scale is a widely accepted gait normality measure based on observation. Considerable efforts have been put into deriving an equivalent measure from kinematic data. Principal component analysis (PCA) on 16 discrete gait variables has been used to create a representation of the data in a different space. The magnitude of the projection of an abnormal data set onto this space is used as a normality index, known as the Gillette Gait Index (GGI) [16]. A very similar PCA approach named the Gait Deviation Index (GDI) has been introduced by [17]. One advantage of PCA approaches is that they transform the possibly dependent gait variables into a new set of independent variables. The disadvantage is that results cannot be traced back to the original gait variables.

A much simpler method, the Gait Profile Score (GPS) and Movement Analysis Profile (MAP), has been suggested [18]. The MAP is created by taking the root mean square error (RMS) between a reference joint angle curve and the corresponding curve from a subject. This creates one normality index for each joint angle curve. A unique index, the GPS, can be derived by concatenating all joint angle curves end to end, and taking the RMS of this aggregated curve. Although the GDI presents some nice properties such as normal distributions across GFAQ levels, the GPS is more easily interpreted because the original variables suffer no transformations and results are given in degrees. It has been shown that the GPS correlates significantly with clinical judgment [19].

### 2.3 Instrumented Gait Analysis

Inertial sensors, such as accelerometers and gyroscopes, can complement MOCAP systems and OGA by providing quantitative and objective gait measurements outside the gait lab, and for a fraction of the cost.

Most symmetry measures calculated from inertial sensor data take into account only discrete spatio-temporal variables, e.g. [20], [21]. Although discrete symmetry indices have been shown useful, a more informative measure of symmetry may be obtained using the entire continuous sensor data. Few approaches to calculating symmetry using continuous accelerometer data have been introduced. One example is an unbiased autocorrelation method using trunk acceleration data [22]. Although this may provide a good general estimate of gait symmetry, it lacks information about each individual limb.

More recently, gyroscopes data obtained from shanks and thighs was used to calculate symmetry using a normalized cross correlation approach [23]. This method segments and normalizes the data to individual strides. As a result, only the shape of the signal and not its relative temporal characteristics are taken into account. A symbolic method for estimating gait symmetry using accelerometers [24] or gyroscopes [25] has been suggested, which takes into account not only the shape but also the temporal characteristics of the signal. This symmetry measure is used in the present paper.

Based on this symmetry measure, the authors proposed a normality measure based on symbolized inertial sensor data, described in the present paper. No other normality measures based on inertial sensor data were found in the literature.

# 3 Method

The study was conducted in two phases. The first phase was an in-lab evaluation that compared the proposed mobile GA system with 3D kinematic analysis. The second, was an in-situ evaluation of the proposed system against quantitative and qualitative clinical assessments of hip-replacement patients. This study was approved by the Regional Ethics Board in Gothenburg, Sweden.

## 3.1 In-Lab Data Collection

The data collection took place at the clinical gait lab at Sahlgrenska University Hospital, Gothenburg, Sweden. A group of 19 healthy volunteers participated in the study. The average hight of the group was 172.1 ± 7.6 cm; and the average weight was 71.8 ± 17.2 Kg. Seven participants were male and twelve female, averaging an age of 34 ± 13 years.

Kinematic and kinetic data were recorded with a 3D motion capture (MOCAP) system, Qualisys MCU 240, sampling at 240Hz. A total of 15 spherical reflective markers, of 19 mm in diameter, were placed on the sacrum, anterior superior iliac spine, lateral knee-joint line, proximal to the superior border of the patella, tibial tubercle, heel, lateral malleolus and between the second and third metatarsals [26].

Subjects were also equipped with 3 Shimmer® sensor nodes, each containing one 3-axis accelerometer and one 3-axis gyroscope, sampling at 128Hz. One node was placed on each outer shank, about 3cm above the lateral malleolus, Figure 1. The remaining node was placed mid-way between the anterior superior iliac spine markers, Figure 2. Sensors were synchronized using a beacon signal from the host computer, and the data was stored on-board each sensor node.

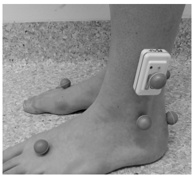

**Fig. 1.** Shank sensor node approximately 3cm above the lateral malleolus

**Fig. 2.** Waist sensor node mid-way between the anterior superior iliac spine

The subjects' movements were simultaneously recorded with the sensor nodes and with the Qualisys system. They were instructed to walk in 3 different ways: 1) normally at a comfortable speed; 2) with a limp, as if injured; and 3) slowly, as if very tired. All subjects performed three tests for each type of walk. One test of each type was then randomly chosen for further analysis.

## 3.2 In-Situ Data Collection

This data collection took place at the orthopedic ward at Sahlgrenska University Hospital, Mölndal, Sweden. Eleven patients were included in the study. All patients had undergone unilateral hip-arthroplasty for the first time and presented no other physical or cognitive conditions. The group was composed of four women and seven men, the mean age was 69$\pm$15 years, mean weight was 81$\pm$20 Kg, and mean height was 172$\pm$9 cm.

All subjects were equipped with sensor nodes similarly to the in-lab data collection. They were then asked to walk by themselves along a 10-meter walkway at a comfortable speed, twice. The walkway was marked with black tape on the floor. The time and number of steps taken to complete the walkway were recorded.

This procedure took place on the day the patient was discharged from the hospital, and a few months later, when the patient came back for a follow-up evaluation. The average number of days spent at the ward after surgery was 4$\pm$1 day. The time between baseline and follow-up measurements was 108$\pm$15 days. All patients employed a walking aid during baseline measurements, six used two crutches and five used a walker with wheels. During follow-up measurements six patients used one crutch and five patients walked without any aiding device.

Patients filled out an EQ-5D™ health questionnaire (Swedish version) approximately two weeks before surgery, and soon after their follow-up session. The EQ-5D™ is a standardized instrument for measuring health outcome, developed by the EuroQol Group (www.euroqol.org). The English version of the questionnaire, validated for Ireland, is shown in Figure 3. Each answer is given a value from 1 to 3, lower values indicate better health.

### 3.3 Observational Gait Analysis

The time, $Tm$, and number of steps, $NumSteps$, taken to complete the 10-meter walk test were used to compute average speed, $Speed = 10/Tm$ (m/s), and average step length, $StepLeng = 10/NumSteps$ (m). In addition, step length was normalized by the patient's height. These variables were used as reference for the improvement of the patient, under the assumption that average speed and step length should increase as the patient recovers.

### 3.4 MOCAP Gait Analysis

Gait normality and symmetry measures were calculated from the 3D kinematic data. The normality index used for the kinematic data was the GPS and the MAP [18]. However, the mean value was removed from all curves before calculating the score, and foot progression was not used because it was not available in the reference data set. Removing the curves' mean values makes the normalcy measure more robust to offset errors, while preserving the shape and range of the curves.

The reference data set was an ensemble of 34 randomly selected adult subjects presenting no known pathologies, previously acquired at the clinical gait lab at Sahlgrenska University Hospital, Gothenburg, Sweden. Joint angle curves were calculated for each individual and normalized to stride time. The ensemble average of the normalized curves was used as a reference curve.

Each MAP component, Eq. 1, was calculated as the RMS difference between the reference curve, $C_{ref}$, and the subject's curve, $C_{subj}$, where $N$ is the number of points

| | |
|---|---|
| By placing a tick in one box in each group below, please indicate which statements best describe your own health state today. | |
| **Mobility** | |
| I have no problems in walking about | 1 |
| I have some problems in walking about | 2 |
| I am confined to bed | 3 |
| **Self-Care** | |
| I have no problems with self-care | 1 |
| I have some problems washing or dressing | 2 |
| I am unable to wash or dress myself | 3 |
| **Usual Activities** | |
| I have no problems with performing my usual activities | 1 |
| I have some problems with performing my usual activities | 2 |
| I am unable to perform my usual activities | 3 |
| **Pain/Discomfort** | |
| I have no pain or discomfort | 1 |
| I have moderate pain or discomfort | 2 |
| I have extreme pain or discomfort | 3 |
| **Anxiety/Depression** | |
| I am not anxious or depressed | 1 |
| I am moderately anxious or depressed | 2 |
| I am extremely anxious or depressed | 3 |

**Fig. 3.** EQ-5D™ English version validated for Ireland. *©1990 EuroQol Group EQ-5D™ is a trademark of the EuroQol Group.*

in the curve. The GPS was calculated similarly by concatenating all joint curves end to end. For each subject, MAP and GPS results were calculated as the average between right and left sides.

$$MAP = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(C_{subj}(n) - C_{ref}(n))^2} \tag{1}$$

Based on the GPS, a measure of symmetry was derived for the kinematic data. In this case, the components of MAP-symmetry were calculated as the RMS error between the curves for the right and left sides, after removing their corresponding mean values. Similarly, GPS-symmetry was calculated by concatenating all joint curves end to end and calculating the RMS difference between left and right sides.

### 3.5 Instrumented Gait Analysis

The symmetry measure used in this paper was presented in [25]. The sensor signal, accelerometer or gyroscope, was standardized to zero mean and unitary standard deviation, then segmented into $N$ symbols. Symbolization is done by quantization into $N$ levels. The quantization levels are chosen based on the empirical probability distribution of the signal, so as to produce equi-probable symbols.

The period between consecutive occurrences of the same symbol are calculated and stored in a *period histogram* [25]. Similarly, the period between symbol transitions of the same type may be stored in a *transition histogram*. The symmetry index is a measure of the similarity between symbol period (transition) histograms for the right and left sides. Histograms are compared using a relative error measure shown in Eq. 2, where $Z$ is the number of symbols; $K$ is the number of bins in the histograms; $n_i$ is the number of non-empty histogram bins (for either foot) for symbol $i$; $h_{Ri}(k)$ is the normalized value for bin $k$ in the period histogram $i$ for the *right* foot; and $h_{Li}(k)$ is the normalized value for bin $k$ in the period histogram $i$ for the *left* foot.

$$SI_{symb} = \frac{\sum_{i=1}^{Z} \frac{1}{n_i} \sum_{k=1}^{K} |h_{Ri}(k) - h_{Li}(k)|}{\sum_{i=1}^{Z} \frac{1}{n_i} \sum_{k=1}^{K} |h_{Ri}(k) + h_{Li}(k)|} 100 \qquad (2)$$

The normality measure for the inertial sensor data was derived from the symmetry measure. Instead of comparing the histograms for right and left sides, one subject's histograms are compared to histograms derived from a reference data set. The reference data set was formed by selecting the (in-lab) subjects that presented the smallest GPS based on the normal walk kinematic data.

The normal walk inertial sensor data from these reference subjects was standardized to zero mean and unitary standard deviation, symbolized, and symbol periods were calculated. The symbol periods were normalized to stride time. That is, a period that coincides with stride time is represented as 1 and all other periods are scaled correspondingly. This normalization is common when dealing with kinematic data, and it ensures that the analysis is not affected by gait speed. The symbol periods from all reference subjects were used to create reference histograms.

### 3.6 Data Analysis

The data acquired from the MOCAP system was processed in Visual 3D (C-Motion Inc., Germantown, MD) to generate kinematic join angle data and spatio-temporal parameters such as stride time. The data was then exported to MATLAB (MathWorks, Natick, MA) where MAP, GPS, MAP-symmetry and GPS-symmetry were calculated for each subject.

The signals from the shank accelerometers and gyroscopes were low-pass filtered with a Butterworth filter of order 6 and cut-off frequency 20Hz. The waist sensor data was filtered at 10Hz. The signals were filtered once, then reversed and filtered again to avoid any phase shift. The three axes of each accelerometer were combined into a resultant signal, $A_{res} = \sqrt{A_x^2 + A_y^2 + A_z^2}$. For each gyroscope, only pitch and roll rotations were considered, $G_{res} = \sqrt{G_{pitch}^2 + G_{roll}^2}$.

Symmetry was calculated using right and left shank signals. Normality was calculated using both shanks and waist signals. Measures were calculated considering period and transition histograms, using from 5 to 25 symbols. The resulting values outside two standard deviations were considered outliers and removed. The remaining values were used to calculate the Spearman's rank correlation coefficient with kinematic measurements, MAP, GPS, MAP-symmetry and GPS-symmetry. The optimal number of symbols was chosen so as to maximize the correlation coefficients. These optimal parameters were used to calculate symmetry and normality for the hip-replacement patients.

The Spearman's rank correlation coefficient was used to evaluate the correlation between two variables. The non-parametric Wilcoxon rank sum test was used to compare two distributions, and a Kruskal-Wallis test was used to compare more than two distributions. All linear model approximations were calculated based on least mean square errors.

The area under the receiver operating characteristic curve (AUC) was used to evaluate the discriminatory power of the normality index. The ROC curve was constructed based on tests performed on the same individuals. Therefore, any statistically significant comparison between different AUC must take into account the correlated nature of the data. A nonparametric approach based on generalized U-statistics was used to estimate the covariance matrix of the different curves [27].

All measurements of the in-situ data collection included two trials, which were used to assess the test-retest reliability of each index using intra-class correlation coefficient (ICC) type A-1 as a measure of absolute agreement [28]. All tests were bi-directional with confidence level, $\alpha = 0.05$. All data analysis was undertaken in MATLAB (MathWorks, Natick, MA).

# 4 Results

## 4.1 In-Lab Evaluation

The best correlation of MAP and GPS with the proposed normality index was achieved with the waist accelerometer sensor, 18 symbols and transition histograms. The best correlated signals are shown in Table 1. The best correlation of the inertial sensor symmetry with MAP-symmetry and GPS-symmetry was achieved with the shank gyroscopes, 20 symbols, and symbol period histograms. The best correlation coefficients are shown in Table 2. These configurations were used to calculate normality and symmetry respectively in the in-situ evaluation.

## 4.2 In-Situ Evaluation

All but one participant answered the EQ-5D™ questionnaire on both occasions. The values of the answers given to each category were added to a single score for that category. Results from before the operation and after the follow-up session are shown in Figure 4. Lower scores correspond to more patients in better health. The biggest changes were regarding mobility, usual activities and pain/discomfort.

Symmetry results for baseline and follow-up measurements are shown in Figure 5 for each subject. Measurements were averaged over both trials of each session. The symmetry index ranges from 0 to 100, a low symmetry index indicates good symmetry whereas a high value indicates asymmetry. According to the proposed index, gait symmetry improved at follow-up for approximately half the subjects. The asymmetry at follow-up may be caused by the use of one crutch. The symmetry index according

**Table 1.** Correlation of MAP and GPS values with the proposed normality measure (waist sensor node)

| sensor | accelerometer | |
|---|---|---|
| placement | waist | |
| histogram | transition | |
| no. symbols | 18 | |
| variable | r | p-value |
| MAP knee flex. | 0.77 | <0.0001 |
| MAP hip flex. | 0.82 | <0.0001 |
| MAP pelv. rot. | 0.71 | < 0.0001 |
| GPS | 0.81 | < 0.0001 |

**Table 2.** Correlation of MAP-symmetry and GPS-symmetry values with the proposed symmetry measure (shank sensor nodes)

| sensor | gyroscope | |
|---|---|---|
| placement | shank | |
| histogram | symbol period | |
| no. symbols | 20 | |
| variable | r | p-value |
| ankle flex. | 0.64 | < 0.0001 |
| knee flex. | 0.81 | < 0.0001 |
| hip flex. | 0.68 | < 0.0001 |
| all | 0.84 | < 0.0001 |

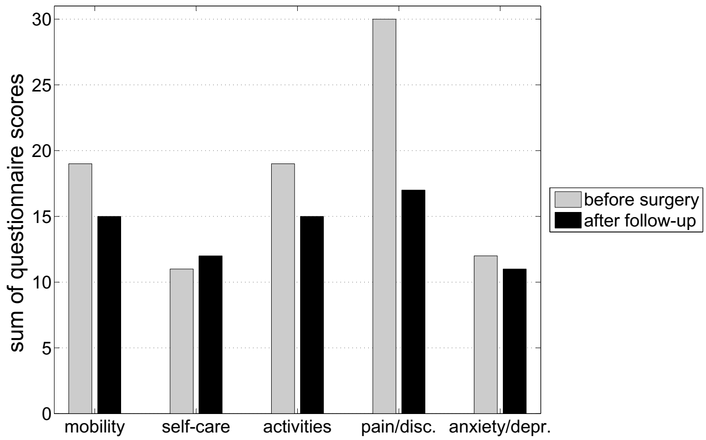


**Fig. 4.** Questionnaire results from before the surgery and after the follow-up sessions. Lower scores correspond to more patients in better health

walking aid is shown in Figure 6. There is a clear difference between the symmetry of patients using two crutches at baseline and patients walking with no aid at follow-up. However, none of the distributions were significantly different.

Normality results are shown in Figure 7, measurements for each patient were averaged over both trials of each session. Similarly, the normality index ranges between 0 and 100, and a low value indicates good normality. In this case, the follow-up measurements were better than baseline measurements for all patients. A Wilcoxon test indicated that baseline and follow-up groups were statistically significantly different, $p<0.0001$. Figure 8 illustrates the distribution of the normality index according to walking aid. As expected, the normality index for those patients walking without aid was, on average, better than the others. A Kruskal-Wallis test indicated that the free walking group was statistically different from the walker and crutches groups, and that the one crutch group was statistically different from the walker group.

In order to calculate the correlation between normality and walking aid, each category was represented by a number. In the order shown in Figure 8, walker was

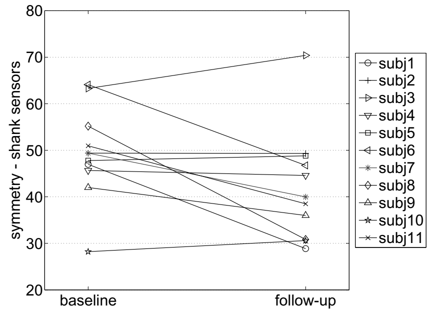


**Fig. 5.** Symmetry results at baseline and follow-up. The two distributions are not statistically significantly different.

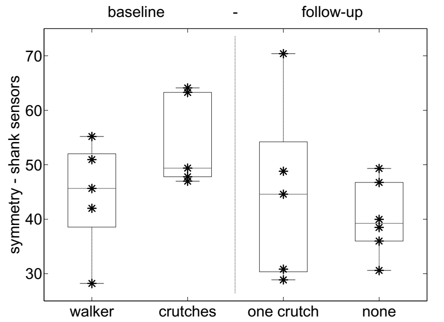


**Fig. 6.** Symmetry results according to walking aid. Box-plot representations of the distributions. The whiskers represent the smallest and largest observations, the edges of the box correspond to the lower and upper quartiles, the horizontal line indicates the median.

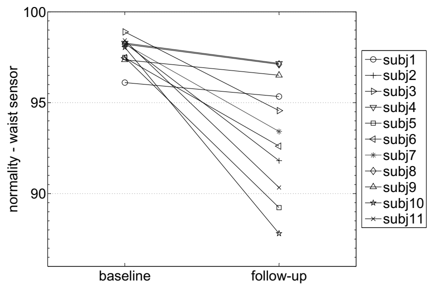


**Fig. 7.** Normality results at baseline and at follow-up. The two distributions are statistically different according to a Wilcoxon rank sum test, $p<0.0001$.

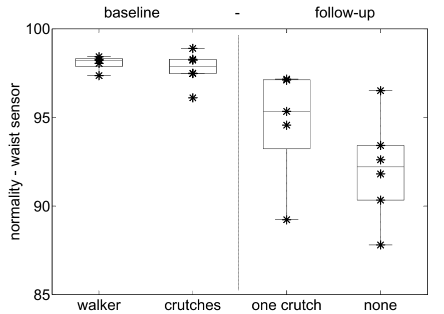


**Fig. 8.** Normality results according to walking aid. A Kruskal-Wallis test indicates that the distribution of no walking aid is significantly different from distributions of two crutches and walker.

represented by 1 and no-aid was represented by 4. The resulting Spearman's rank correlation coefficient was $r=-0.78$, $p<0.0001$.

The normality index also correlates well with both average speed, $r=-0.79$ $p<0.0001$, and normalized average step length, $r=-0.76$ $p<0.0001$. Normality values for each individual trial are shown against average speed values in Figure 9, and against normalized step length in Figure 10. On both plots the linear model approximation is shown as a solid line, and the 95% confidence interval (CI) for predicted observations is shown as dotted lines. The mean average speed at baseline, $0.46\pm0.16$ m/s, was significantly different from the speed at follow-up, $1.06\pm0.22$ m/s, $p<0.0001$.

Normality results were also compared to the EQ-5D™ answers that varied the most between before the surgery and after follow-up, namely mobility (Figure 11), usual activities (Figure 12), and pain/discomfort (Figure 11). In all cases, there is a

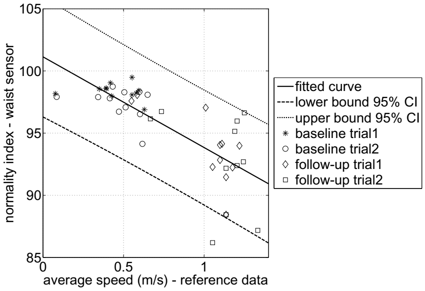


**Fig. 9.** Normality compared to average speed. Variables are well correlated, Spearman's rank correlation coefficient r=-0.79, p<0.0001. The solid line indicates the linear model approximation a+bx, where a=95.5 with confidence interval (CI) [94.9, 96.3]; and b=-2.6 with CI [-3.3, -1.9]. The dashed and dotted lines indicate the 95% CI of predicted observations.

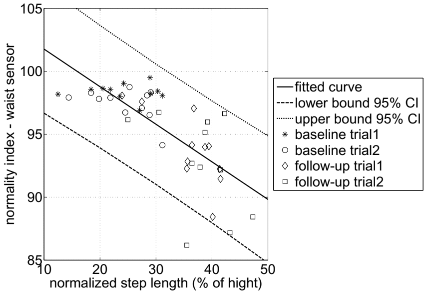


**Fig. 10.** Normality compared to average step length. Variables are well correlated, Spearman's rank correlation coefficient r=-0.76, p<0.0001. The solid line indicates the linear model approximation a+bx, where a=95.5 with confidence interval (CI) [94.9, 96.3]; and b=-2.5 with CI [-3.2, -1.8]. The dashed and dotted lines indicate the 95% CI of predicted observations.

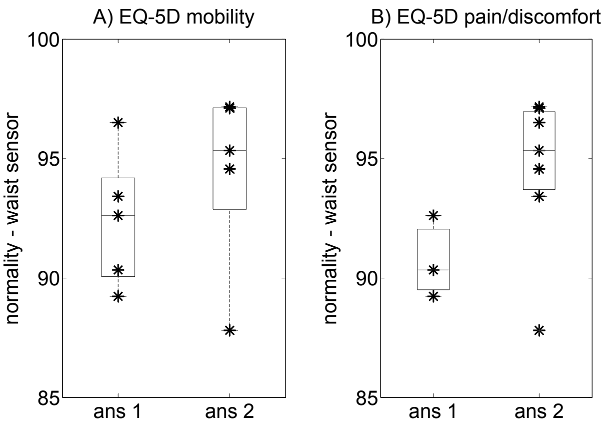


**Fig. 11.** Normality compared to EQ-5D™ answers regarding (A) mobility and (B) pain/discomfort. Mobility answers - ans 1: I have no problems in walking about; ans 2: I have some problems in walking about. Pain/discomfort answers - ans 1: I have no pain or discomfort; ans 2: I have moderate pain or discomfort.

tendency for better health to be accompanied by better normality index. This correlation is particularly strong between normality and usual activities scores, Spearman's r=0.75, p=0.0127. There was no correlation between the health scale in Part B of the questionnaire and normality.

Improvement in normality was calculated as the difference between baseline and follow-up values. Figure 13 shows how improvement in normality correlates with number of days spent at the ward after surgery. Although a Wilcoxon test indicated that there was no statistically significant difference between groups, the Spearman's rank

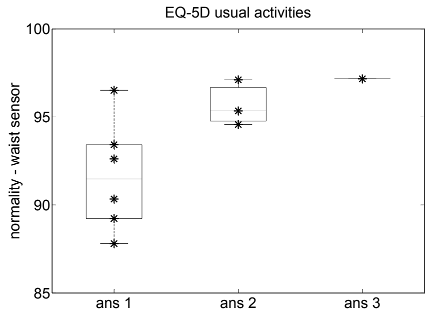


**Fig. 12.** Normality compared to EQ-5D™ answers regarding usual activities. Ans 1: I have no problems with performing my usual activities; ans 2: I have some problems with performing my usual activities; ans 3: I am unable to perform my usual activities.

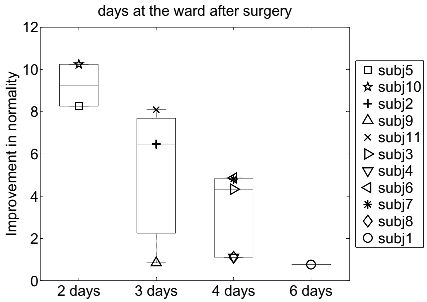


**Fig. 13.** Improvement in normality compared to days spent at ward after surgery. Improvement in normality is the difference between normality values at baseline and at follow-up. Although the distributions are not statistically different, variables are well correlated, Spearman's rank correlation coefficient r=-0.75, p=0.0081.

correlation coefficient was r=-0.75, p=0.0081. There was no correlation between improvement in normality and days between baseline and follow-up sessions.

The normality index can also be evaluated based on its discriminatory values. That is, the ability to differentiate baseline measurements from follow-up measurements. The AUC was 0.94, confidence interval (CI) (0.87, 1.00), p<0.0001. The test-retest reliability was also high, r=0.81, CI (0.60, 0.92), p<0.0001.

## 5 Discussion

The in-lab evaluation confirmed that the proposed measures of normality and symmetry are well correlated with the kinematic measures, namely MAP, GPS, MAP-symmetry and GPS-symmetry. The found optimal parameters were used for the in-situ evaluation. The remaining of this section discusses the results of the in-situ evaluation.

The average speeds at baseline and follow-up are in agreement with measurements reported in [29], 0.46 m/s less than 16 days after hip replacement surgery and 1.17 m/s more than 20 days after surgery. Average gait speed of approximately 1 m/s three months after surgery were also reported in [30]. According to [31] the greatest improvements in gait speed are observed within the first three months post-op. The follow-up measurement can, therefore, be considered representative of patient's improvement in gait speed. In addition, [32] determined that changes in speed superior to 0.10 m/s are clinically meaningful after hip fracture treatment. The changes in speed observed from baseline to follow-up, $0.60 \pm 0.29$, are therefore also clinically meaningful.

Measures of gait normality correlate well with both gait speed, Figure 9 and step length, Figure 10. Given that speed and step length are measures related to patient recovery, there is a good chance the normality index is also a good indicator of recovery. Unfortunately, no other quantitative gait parameters were available in the data set to demonstrate that the normality index correlates to recovery when the data is corrected for speed. However, in Part I of this study symmetry and normality measures are shown to correlate to joint-angle curves normalized to stride time, not containing any velocity information. The normality index is also normalized to stride time and as such is independent of walking cadence. It is expected that the normality index would differentiate between normal and abnormal patterns at the same speed. Further investigations are needed to support this assumption.

Another factor supporting the usefulness of the normality index is its correlation with the type of walking aid used during the test, Figure 8. The test-retest reliability and discriminatory power of the index were also satisfactory. Overall, the proposed index can possibly be developed into a reliable and clinically relevant measure of gait normality.

Another interesting result was the correlation between improvement of normality and number of days spent at the ward, Figure 13. Whereas there was no correlation between improvement in normality and number of days between baseline and follow-up. This possibly suggests that the rate of recovery at the ward is indicative of the total rate of recovery, which is little affected by the recovery time at home. This assumption should be further investigated.

Normality results and the answers to the EQ-5D™ questionnaire showed some positive trends. Greater discomfort and difficulties in performing usual activities seem to be accompanied with worse normality, Figure 11. Besides the self-assessment questionnaire, the use of walking aids was also considered an indication of how well the patient's health status was, i.e. patients who did not need any walking aid were, on average, in better condition than those who used one crutch. Another indicator of recovery was the number of days the patient spent at ward, assuming that patients who recovered better or more quickly were discharged sooner. The normality index seems to be in agreement with all the above mentioned qualitative health status assessments.

Symmetry results are difficult to judge due to the variety of walking aids used. The large variety of symmetry at follow-up, Figure 5, was mostly influenced by the patients using one crutch only. This could be explained by the fact that some patients were more dependent on the crutch and consequently leaned more to one side. Whereas some patients barely used the crutch for support.

Due to their recent surgery, patients were very uncomfortable during the baseline measurements. It was important to keep the data collection as simple and quick as possible. No more than five minutes had to be spared by the patient to complete the entire procedure, and they were all willing to participate in the study. Briefness is also important for the staff responsible for the procedure so that the addition of GA is not an extra burden. The placement of the sensors was also quick and easy. However, in the future, the waist sensor should be placed on the lower back so as not to be affected by subjects' different shapes and sizes.

Another issue with the present study is that the number of participants was very small. Any statistical inference on the results is greatly affected by the sample size. However, results are promising and suggest that a larger study will likely produce positive results.

At the ward where the data was collected, gait analysis is not normally used, and most records are based on rough qualitative descriptions. This lack of quantitative measures makes the assessment of patient improvement a difficult and very subjective task. The introduction of a simple 10-meter walk test can already provide quantitative measures of speed and stride length. The addition of a wearable GA system, however, can quickly increase the amount of quantitative data to include more complex measures of symmetry and normality.

## 6 Conclusions

The present study investigated the use of inertial sensors for quantitative GA, both in-lab and in-situ. The proposed system served as a tool to facilitate the extraction of certain gait characteristics, namely symmetry and normality. The system was evaluated against 3D kinematic measures of symmetry and normality, as well as clinical assessments of hip-replacement patients. Not only was the proposed system in agreement with kinematic variables but it also correlated well with the level of recovery and health status of the patients in a very intuitive way. This study showed that such a system may be deployed in a real clinical environment in order to aid current clinical assessment by incorporating quantitative GA.

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