Observing Recovery from Knee-Replacement Surgery by using Wearable Sensors

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***Abstract*—A progressive improvement in gait following knee arthroplasty surgery can be observed during walking and transitional activities such as sitting/standing. Accurate assessment of such changes traditionally requires the use of a gait lab, which is often impractical, expensive, and labour intensive. Quantifying gait impairment following knee arthroplasty by employing wearable sensors allows for continuous monitoring of recovery. This study employed a recognised protocol of activities both pre-operatively, and at regular intervals up to twenty-four weeks post-total knee arthroplasty. The results suggest that a wearable miniaturised ear-worn sensor is potentially useful in monitoring post-operative recovery, and in identifying patients who fail to improve as expected, thus facilitating early clinical review and intervention.**

***Index Terms*—Wearable sensors, body sensor networks, gait.**

I. Introduction

Annually, over 400,000 people worldwide undergo knee replacement surgery (arthroplasty). Over 90% of people who have had a total knee replacement experience an improvement in knee pain and function. However, the economic and social cost of knee-replacement does not stop as the patient leaves the operating theatre. In addition to hospital costs, there is a significant cost implication due to continuing care and surveillance during the early post-discharge period [1], [2]. Monitoring patient recovery in follow-up clinics is both labour intensive, and possibly inaccurate given that it relies to a large extent on a clinical examination, and subjective scoring questionnaires. In many cases, patients are asked to attend frequent rehabilitation sessions and lab-based gait assessment. Keeping track of patient improvement over time incurs a significant healthcare cost and developing methods of quantifying gait and motion changes over-time is of extensive interest to all stake-holders.

In the UK, post-operative review by the surgical team is usually undertaken at six, twenty-four, and fifty-two weeks post-op. However, despite guidelines published by the British Orthopaedic Association [4], longer term surveillance is poorly carried out in the UK, and indeed not funded at all in most areas. The causes of early and late failure of knee replacement operations are often not captured by the current out-patient follow-up systems. Early infection of the implant usually presents between 1 and 6 weeks after the operation, where patients are not routinely recalled for outpatient appointments. Early aggressive antibiotic therapy and surgical debridement may eradicate the infection, and avoid costly revision surgery that could involve long hospital stays and significant morbidity to the patients. Late failures of the implants are presented between 5 - 10 years after the operations, and are often silent to the patients. Presently, only clinical and radiological reviews of the patients can recognise these silent failures, which are not performed routinely. Indeed, early identification can help planning revision surgery, before excessive bone loss preventing salvage operations. Furthermore, in a busy outpatient clinic, functional and activity-related outcomes of the patients are not routinely reported. These are perhaps most relevant to the patients, and difficult to monitor in a hospital environment. Difficulties in specific activities, such as climbing stairs, if identified can be referred for early targeted physical therapy to improve the function of the patient.

Given the advanced age of many patients having knee surgery, attempts to quantify patient function postoperatively and objectively observe the effect of ageing on the deterioration of musculoskeletal function are of great interest to clinicians. A questionnaire was suggested by Noble and Weiss [5] to determine the effect of surgery on activities of daily living, especially ones placing greater loads on extremities. The International Physical Activity Questionnaire (IPAQ) is also widely used for assessing health related physical activity in populations [6]. Although questionnaires are widely used as a method of assessing patient function, their limitations for practical use include dependence on patient compliance and recall. The absence of a continuous measure of daily recovery is also a hurdle to overcome as questionnaires and visits to the clinic can only offer snapshots of the patient's state.

The study of gait changes and its role in rehabilitation has been an active area of research and a number of systems have been proposed to study gait irregularities. Most proposed systems for gait observation rely on on direct biomechanical or biomotion measurements. These features can be derived from optical motion tracking [7] or video image sequencing [8]. The features allow quantitative analysis of gait characteristics such as joint moments and powers, joint angles, angular velocities and angular accelerations [9]. Reviews on human motion analysis based on video, including summaries of modelling, tracking and recognition, are provided by Dariush [10] and

	Locomotion	
1	Walk 12 steps	
2	Walk 12 steps back and forth	
3	Walk 12 steps (second time)	
4	Walk a longer distance (30 steps)	
	Rise and descend	
5	Ascend and descend stairs	Start with the unaffected leg
6	Ascend and descend stairs	Start with the affected leg
7	Ascend and descend slope 120 cm long (with 33 % inclination)	Start with the unaffected leg
8	Ascend and descend slope	Start with the affected leg
9	Step up and down a block 20 cm	Up with the unaffected leg
10	Step up and down a block 30 cm	Up with the unaffected leg
11	Step up and down a block 20 cm	Up with the affected leg
12	Step up and down a block 30 cm	Up with the affected leg
	Transfers and getting up	
13	Pick up a 4 kg weight and walk	Pick up with the unaffected side
14	Pick up a 4 kg weight and walk	Pick up with the affected side
15	Sit down and stand up on and from block of 40 cm height	
16	Sit down and stand up on and from block of 30 cm height	
	Lifting and moving objects	
17	Forward slalom with shopping trolley	
18	Backward slalom with shopping trolley	
19	Carry a tray with two cups walking 12 steps	
20	Carry a 4 kg shopping bag walk 12 steps straight	On the unaffected side
21	Carry a 4 kg shopping bag walk 12 steps straight	On the affected side
22	Timed up and Go	Sitting, walk 3 metres, turning then sit again
23	Walk 12 steps (last time)	

TABLE I
THE PROTOCOL PERFORMED BY KNEE-SURGERY PATIENTS DURING VISITS WHILE WEARING THE SENSOR. THE PROTOCOL BUILDS ON THE DYNAPORT® KNEE TEST [3] WHICH IS A PERFORMANCE BASED TEST THAT HAS BEEN VALIDATED WITH OBSERVATIONS BY PHYSIOTHERAPISTS.

Aggrawal *et al.* [11]. Performing these gait tests generally requires patients to attend specialised clinics or gait-labs where they are asked to carry out several activities while being monitored.

An alternative method of observing gait involves the use of miniaturised sensors that can be worn by participants or integrated in home environments providing continuous monitoring over long periods of time. The advances made in hardware miniaturisation, on-node storage and software optimisation mean that these sensors can be worn unobtrusively without affecting patients' daily patterns, thus providing a means of behaviour monitoring [12]. Accelerometers, gyroscopes and force-sensors have both been used on different parts of the body to measure gait parameters [13], [14], [15]. Commonly used parameters for gait monitoring include initial contact (IC) that defines the beginning of a complete gait cycle and thus cycle duration and frequency, and terminal contact (TC) that marks the start of the swing phase. Knee-joint [16] and hip-joint angles [17] have also been calculated by the integration of angular velocity from gyroscopes. Ground reaction forces were measured by force-sensitive insoles to observe impaired gait in [18]. Frequency features observed in accelerometer signals have also been used to observe leg injury [19]. Due to sway, motion irregularity and leg-pain, patients who have undergone knee surgery show changes in both the temporal and frequency domain. These changes are not normally limited to one direction of motion and are observed in walking as well as daily activities such as getting up or sitting down and carrying objects.

This paper builds on the protocol proposed in [3] to observe changes in gait following knee-replacement surgery. A novel ear worn activity recognition (e-AR) sensor [20] is used while performing the protocol activities. The e-AR sensor is selected for this work as it has been shown to efficiently capture the changes of gait due to post-operative recovery and simulated injuries using a knee-brace [21]. Head worn accelerometers can capture increasing activity levels [22] as well as the shock wave reflecting force loading. The work presents a systematic analysis framework and detailed results on a dataset collected from a cohort of knee-replacement patients.

II. EXPERIMENTAL SETUP

Patients on the waiting list for total knee arthroplasty were identified from St Mary's Hospital and Charing Cross Hospital, London. After obtaining written consent, 8 patients were visited 6 times at home once 1 week before the operation, then at 1, 3, 6, 12 and 24 weeks after the operation. Each visit lasted for 45 minutes, where the clinical outcomes were measured and patients performed the protocol given in table I while wearing the e-AR sensor. The protocol builds on the DynaPort® knee test [3], [23] which is a performance based test previously validated with observations by physiotherapists.The protocol was modified to accommodate mobile equipment which could be transported to patients' homes. An Orthopaedic Specialist Registrar or Senior Physiotherapist was present for at least the first two visits to measure clinical outcomes. Demographical data was recorded from all participants, together with validated questionnaires for measuring

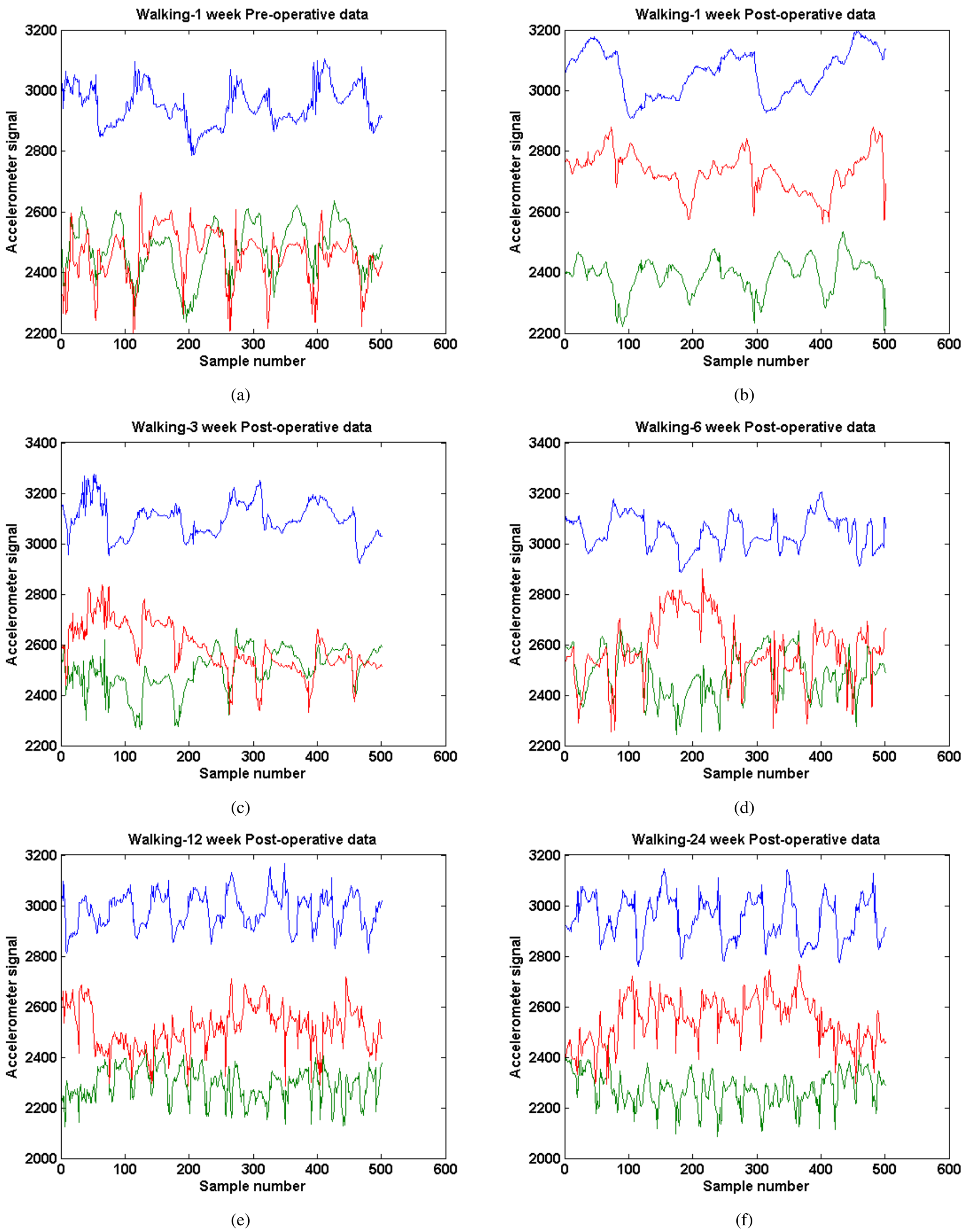


Fig. 1. The figure shows a selected period of walking (10 sec) for a patient 1 week before the knee-replacement operation, then at 1, 3, 6, 12 and 24 weeks after the operation.

knee function including the modified Noble and Weiss Score [5] and the IPAQ questionnaire [6].

In addition to the 8 total knee arthroplasty patients recruited, 10 healthy subjects with no known gait problems were asked to perform the activities given in Table I whilst wearing the e-AR sensor. The sensor is a light-weight device (7.4g) that can be worn on the outer ear cartilage and contains a 3-axis MEMS (Micro-Electro-Mechanical-Systems) accelerometer (ADXL330) which captures the mobility and activity information of the subject. This is wirelessly transmitted to a receiver connected to a laptop/tablet computer in real-time. The ADXL330 accelerometer measures acceleration with a minimum full-scale range of 3g. Analogue to Digital Conversion (ADC) of this data results in x, y, and z axis accelerometer channel outputs ranging from 0-4096, representing 0-3V. A sampling rate of 50 Hz was used in all experiments conducted in this study. The platform used in this work extends the original BSN platform proposed in [24].

III. Analysis Methodology

A. Walking Pattern Analysis by using Wavelets

The analysis method used for walking pattern analysis for this paper is based on wavelet analysis. Wavelets offer a means of observing variations in both the frequency and time-domain that can be indicative of walking gait changes. Their advantage over traditional Fourier analysis is in analysing signals that contain discontinuities and sharp spikes [25]. The Discrete Wavelet Transform (DWT) was selected for this work (as in [21]) as it can provide a compact representation of a signal in time and frequency that can be computed efficiently, compared to using continuous wavelet transforms. The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by successive filtering operations, and the scale is changed by upsampling and downsampling (subsampling) operations. DWT usually uses a dyadic grid.

The DWT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions, called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively. Passing the signal through these filters is also known as sub-band coding. At every level, the filtering and subsampling result in half the number of samples and double the frequency resolution. The most prominent frequencies in the original signal appear as high amplitudes in that region of the DWT signal that includes those particular frequencies. Thus, low walking frequencies such as that of the gait-cycle appear in low frequency scales, whereas high-frequency scales pick-up more subtle motions as well as ground reaction forces.

In this work, the DWT coefficients were calculated for 3-D acceleration data using the 4 coefficient Daubechies wavelet family. Wavelet coefficients were calculated across 4 scales using a moving window that analyses the signal at that window. The window size was empirically selected to be 5 seconds. The mean, $M_{i,j}$ and standard deviation $S_{i,j}$ of wavelet coefficients were extracted per window leading to a feature space of dimension $3 \times J$ where J is the number of wavelet decomposition scales.

In our previous work [21], feature selection was used to observe which features can separate impaired from non-impaired data. The study was performed on a dataset of simulated impairment using a knee-brace versus a dataset of healthy subjects walking on a treadmill and in a corridor. This work uses these features to observe the clustering of data and the variation of clusters over time. The healthy class is modelled as a multidimensional Gaussian using these features. The probability of patient data belonging to this Gaussian is used to assess improvement over time.

B. Detection of Motion during Walking

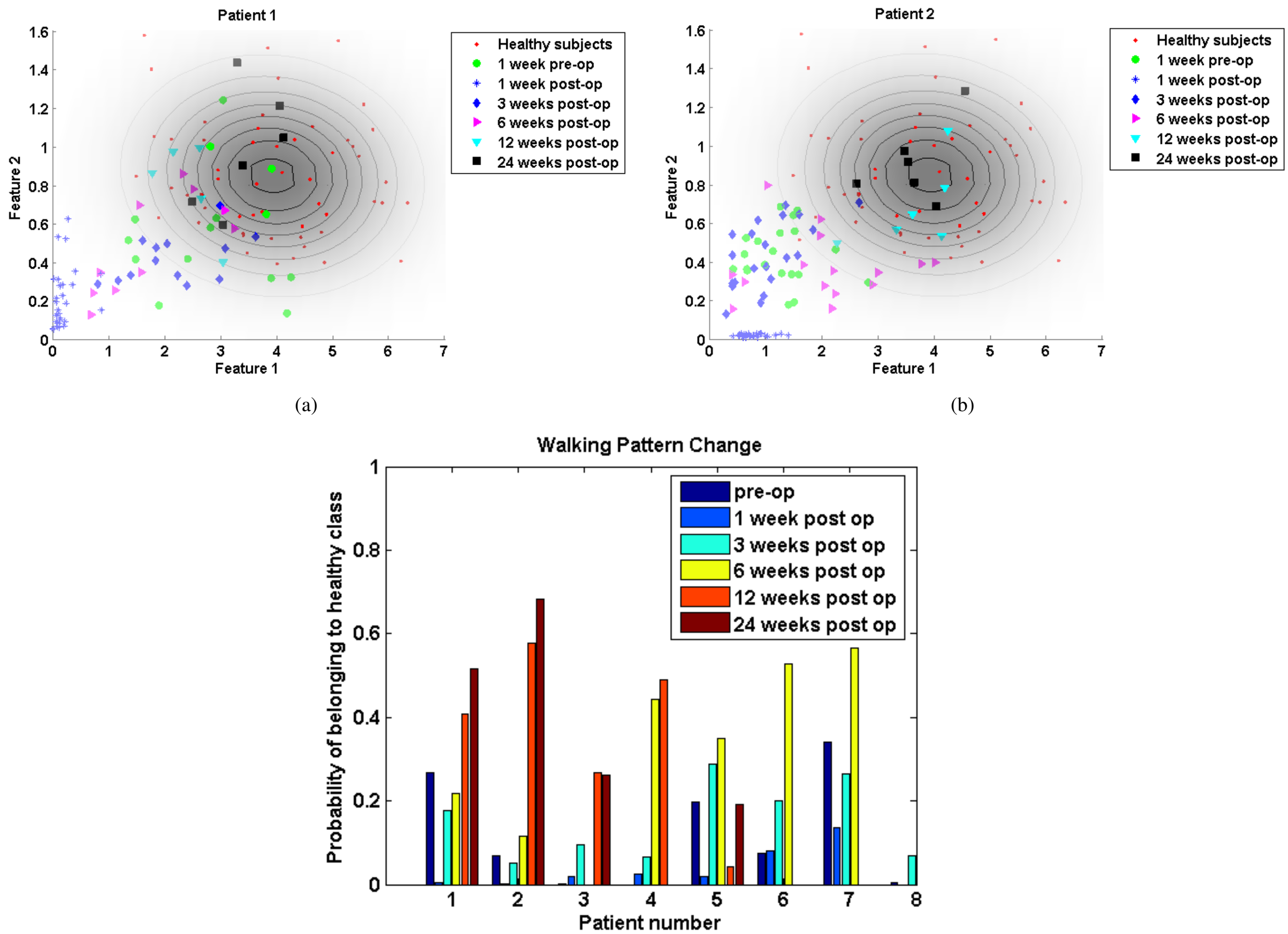
Sway is a parameter that is normally left unmeasured when using pressure sensors only to observe overall mobility. The use of head-worn sensors such as the e-AR sensor allows for observation of overall body sway. A sway imbalance could be indicative of a poorly functioning limb. Likewise, a change in sway over time could be used to monitor changes in walking patterns over the same period. In this study, we used the right-left axis accelerometer data to measure right-left sway.

IV. Results

Figure 1 shows a a ten-second period of walking for a patient 1 week before the knee-replacement operation then for 1, 3, 6, 12 and 24 weeks post-operatively. Post-operatively, the patient demonstrates a slower, and more irregular pattern; most evident in Figure 1(b) (1 week post-op). Patterns become progressively more regular over time; in general, the most regular patterns are observed in week 24 post-op. (Figure 1(f)). Pre-operative data is included for comparison but does not demonstrate a ‘normal’ gait given that the patients have significant knee arthritis warranting arthroplasty. The analysis of pre-operative data should depend on patient condition, age and overall mobility.

Figure 2 shows the variation in walking clusters as patients recover. The features plotted are selected from the wavelet transform according to their optimisation of distances between impaired and non-impaired walking classes [21]. Only two features are selected for illustration purposes. Figures 2(a) and 2(b) show the data for patients 1 and 2 respectively. The gray cluster in both figures shows a 2-dimensional Gaussian modelled on the healthy data for 10 subjects. It is worth noting that although the healthy-walking cluster is distinctive, it presents a lot of inter-subject variations as subjects naturally have different individual gait patterns. The farthest data from the healthy cluster is that of 1 week post-operative data. For both patients, data from weeks 3 and 6 are close. Weeks 12 and 24 show data clustering toward the healthy cluster. Pre-operative data shows a difference between the two patients. Patient 1’s data is close to the healthy data cluster whereas patient 2 was probably struggling with walking pre-operatively as it shows a similarity to 3-6 week post-operative data.

Figure 2(c) shows the averaged probability for feature points for each data collection session to belong to the healthy class.



(a) (b) (c)

Fig. 2. The figure shows the clusters for each week pre and post-operatively for patients 1 and 2 in 2(a) and 2(b) respectively. The probabilities of belonging to the healthy walking cluster are summarised for all 6 patients in 2(c).

Generally, we note that the furthest from the healthy class is 1 week post-operative data. This is consistent for all patients. Data probabilities at weeks 3 and 6 are similar in patients 1 and 5, whereas they are further apart for patients 2, 4, and 6, suggesting different recovery rates. In general, weeks 12 and 24 show higher, more consistent values, indicating that walking patterns are starting to approximate those in healthy subjects. However, outliers exist: walking patterns for subject 5 improved up to 6 weeks post-operatively but then deteriorated, especially at 12 weeks (a review of the clinical notes is underway to look for a possible explanation).

Right-left sway during bag-carrying for all 6 patients as illustrated in Figure 3, reveals that overall, sway appears to increase with improved mobility. In week 1 post-operatively, patients generally demonstrate restricted motion and decreased sway.

V. Conclusion

This study demonstrates a method for observing post-operative recovery after knee-replacement surgery. Instead of defining fixed parameters that may identify normal and impaired walking, we used a wavelet decomposition of 3-D acceleration signals to observe changes in motion reflected in all axes. The method uses data clustering to observe both recovery over time, and progressive approximation to a healthy control group. The study also demonstrated progressive changes in walking sway in the post-operative recovery period.

The changes in walking patterns over time could provide clinicians with a method of remotely observing patients avoiding having to assess patients in a gait lab. With regards to monitoring post-surgical recovery, patient groups such as the elderly or those with comorbidities may in this way be allowed to recover at home with a means of keeping track of their progress and intervening where necessary. At a time when health care cost is under significant financial pressure and hospital readmission is neither cost-effective nor desirable, this work offers an efficient monitoring tool and a tangible way forward for improved patient care after knee surgery.

Limitations of this study include the number of patients

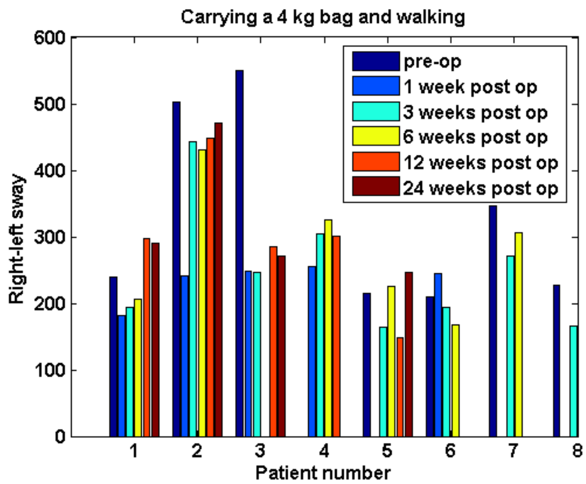


Fig. 3. Right-left sway while carrying an 4 kg weight for all patients pre and post-operatively.

selected. Larger scale studies are required to validate the sensor and assess its features with respect to age, clinical condition and exacerbations. In addition to walking, which is analysed in this work, the protocol included many activities of transitional nature such as stepping and sitting. Our next step will be to observe patient recovery through these activities, in addition to walking. We also aim to cross-validate our sensor with patient notes and measurements of leg flexibility that were measured during the patient visits.

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