# Supporting Rehabilitation After Hip Replacement with a Mobile Device Carried in a Pocket

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#### Abstract

Hip replacement surgery is a procedure undertaken to relieve pain and restore function of a hip joint. Rehabilitation after a hip replacement surgery can last several months. Currently, orthopedists lack information about patients' rehabilitation progress and rely solely on subjective observations in order to decide for a treatment. Previous research on the field of hip replacement surgery has studied the use of wearable sensors to warn patients about movements that could lead to hip dislocation. In this work, we use a mobile device as a means to gain information about the rehabilitation progress after a hip replacement. Results from a study conducted with 12 patients of hip replacement indicate that our approach can classify the kind of walking aid used by patients with an accuracy of 93.3% and provide a gait score that correlates to standard gait scores used by physical therapists with an accuracy of 99.1%.

## ACM Classification Keywords

J.3 [Computer Applications]: Life and Medical Sciences

# Introduction

Hip replacement surgery is a procedure undertaken to relieve pain and restore function of the hip joint affected by osteoarthritis or injury. During the surgery, an artificial joint is implanted to replace the affected hip. Rehabilitation after hip replacement starts on the day of the surgery or the day

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

UbiComp/ISWC'17 Adjunct, September 11–15, 2017, Maui, HI, USA. © 2017 Copyright is held by the owner/author(s). ACM ISBN 978-1-4503-5190-4/17/09...\$15.00. https://doi.org/10.1145/3123024.3124436 after it and involves standing up, walking and performing physical exercises.

Currently, patients recovering from hip replacement surgery perform rehabilitation exercises mostly unsupervised and lack ways to measure the quality and track performance of their rehabilitation. Orthopedists also lack ways to objectively assess patients' rehabilitation progress and still rely on subjective observations to decide on the treatment. Furthermore, the lack of objective ways to quantify a patient's condition causes disagreement between patients and orthopedists as to what the most appropriate treatment should be.

Different approaches for rehabilitation using wearable devices have been explored in the past. These studies have been applied to diverse user groups, including patients of: knee injury [4, 8, 2], Parkinson disease [6, 7], brain stroke [3] and elderly patients prone to fall [1]. In this work, we focus on patients recovering after a hip replacement surgery. Iso-Ketola et al. [5] developed a wearable device for patients of hip replacement that consists of seven sensors distributed around the user's body. The device warns patients of hip replacement about movements that could lead to hip dislocation and measures the amount of load patients bear on their operated legs.

In this work, we explore the use of a mobile device to support rehabilitation after hip replacement surgery. Our goal is to gain insight into a patient's health condition in an unconstrained environment using only the sensors available in a mobile device that is carried by the user in a pocket. The contribution of this paper is threefold. First elicit the requirements for a system to support orthopedists at treating patients of hip replacement. Second, we describe an approach to elicit information about a patient's health condition and rehabilitation progress using a mobile device. Third, we describe an experiment we conducted in order to measure the reliability of the information gathered by our approach.

## Background

In order to elicit the requirements of a system to support rehabilitation after a hip replacement, we conducted a series of interviews with two orthopedists who perform hip replacement surgery on a daily basis and a physical therapist specialized in rehabilitation after hip replacement. The interviews were conducted at the hospital "Barmherzige Brüder" in Munich, Germany, which is specialized on joint replacement procedures. In this hospital, over 1500 hip replacement surgeries are performed per year. We gathered the information that follows.

Patients might follow different kinds of treatments after a hip replacement surgery, depending on their condition. Some patients might stay at the hospital for a few weeks, others might be sent home and visit an outpatient rehabilitation center daily and others might be sent home and attend regular physical therapist sessions. Treatments suited for patients in a worse condition are more costly. Orthopedists are interested in finding the treatment for each patient that minimizes cost and maximizes patient's rehabilitation progress.

Orthopedists suggest patients to follow a treatment based on their experience. Parameters orthopedists take into consideration for the treatment suggestion include the age of a patient, comorbidity and their stability while walking. The decision for a specific treatment is then discussed with patients. According to the stakeholders we interviewed, patients often prefer to stay at the hospital for longer periods of time than considered necessary by orthopedists. However, orthopedists lack of objective data about patients' condition in order to argue for a specific treatment.

According to orthopedists, an important indicator of patients' health condition is the amount of walking they performed daily. Furthermore, patients use different kinds of walking aids, including crutches, walking frames and canes. Most patients use crutches for a few days or weeks after the surgery and progressively start walking without walking aid. However, some patients prefer walking frames or canes. The kind of walking aid and amount of walking provide information about a patient's condition. For example, patients who need a walking frame are considered by orthopedists to be in a worse condition than those who use crutches or a cane. Orthopedists are interested in keeping track of the amount of walking patients perform daily using each type of walking aid.

Rehabilitation after hip surgery usually starts on the day of the surgery or the day after and involves physical therapy. Physical therapists supervise patients and document their progress daily with a *gait score* from 0 to 5. However, physical therapists sometimes disagree on the score that should be assigned to a patient. Orthopedists are interested in a measurement for patients' gait score that does not depend on the subjective observations made by physical therapists.

After the surgery, patients prefer to wear loose garments due to pain and reduced mobility. Therefore, a mobile device placed in the user's pockets might be subject to a high degree of noise. Furthermore, the mobile device might be carried in different types of garments. Some patients do not wear pants but a pijama with a robe on top. An approach to extract relevant information based on a mobile device inside patients' pockets should be able to deal with highly noisy data.

# HipRApp

We introduce HipRApp (Hip Rehabilitation App), an approach that uses a mobile device's integrated motion sensors to elicit information about the condition of a patient of hip replacement surgery. In particular, HipRApp calculates and keeps track of the amount of time patients spent walking per day, the type of walking aid they used and their gait score. This information can be used by orthopedists to gain insight into a patient's condition.

A walking pattern changes significantly depending on the type of walking aid used. Therefore, HipRApp first determines the type of walking aid being used and then it analyzes the walking pattern to calculate the score. This is done with a two step supervised classification. The first classification classifies movement into: walking normally and walking with crutches while ignoring time segments while the patient has not been moving. The second classification classifies gait scores in a scale from 0 to 5.

The signal features used for both classifications are computed in a series of steps: preprocessing, step segmentation and feature extraction.

#### Preprocessing

Data is processed in windows of 45 seconds (4500 samples). In order to remove noise in the signal, we apply a second order Butterworth low-pass filter at 20 Hz to each window. After applying the filter, we compute the magnitude of each linear acceleration vector. This produces a total of 7 data sets: linear acceleration and rotation along three axes and magnitude of linear acceleration.

#### Step Segmentation

The purpose of the step segmentation is to detect whether a step has occurred and if it did occur, determine it's beginning and ending. Step segmentation is done as follows:

- Every step has two upper peaks. We detect the highest peak with a peak detection algorithm. We ignore peaks that are less than 60 samples away from a previously detected peak. This also filters out periods when patients were standing.
- Every step is preceded by periods of small variance in acceleration. We find these periods by searching for the 9-sample window with smallest variance in acceleration among the 70 samples before and after the detected peak.
- 3. Between two step segments, additional samples are included that might not belong to a step. Therefore, we trim the step by shifting the step segments to-wards the peak detected in step 1. The step segments are shifted until the standard deviation of a 6-sample window centered at the shifted step segment is larger than 0.2.

#### Feature Extraction

For each step segmented, we compute a set of gait and statistical features. Gait features are measurements specific of a step. Every step is characterized by three peaks: two upper peaks and one lower peak. We first detect all three peaks. If any of the peaks could not be found, we ignore the step. For all three peaks, we compute its rise value and time. The rise times are computed as the difference in samples to the previous peak. The rise time of the first peak is computed as the difference in samples to the step start. In addition, the total duration of the step is added to the feature set.

Statistical features are measures to extract information from data sets. We extract the following statistical features: mean, median, standard deviation, Zero Crossing Rate (ZCR), Peak-to-Peak amplitude (P2P), Root Mean Square (RMS) and Average Acceleration Variation (AAV) for every step. P2P is the difference between the maximum and minimum acceleration value in a step and provides information about the intensity of a step. RMS is the square root of the mean of the values in a step squared. This measurement provides information about the amount of acceleration and variation in a step. AAV is calculated as the sum of the absolute differences between consecutive samples in a step normalized by the number of samples. AAV provides an indication of how sudden changes in acceleration happen within a step. These measurements are commonly used for activity recognition applications and have been successfully used for fall-detection and gait analysis in humans [3, 1].

Gait features are computed on linear acceleration and statistical features are computed on linear acceleration, rotation and magnitude. ZCR is only computed on the linear acceleration. This gives us a total of 21 gait features and 45 statistical features per step. A window might contain several steps. We average the features extracted from the same window.

## Evaluation

In order to evaluate HipRApp, we conducted an experiment with 12 patients after hip replacement surgery.

#### Setup

We selected patients to maximize diversity of age and health condition. The average age of our subject group was 67 years old, whereas the youngest patient was 44 and the oldest 86 years old. Patients walked with crutches (7) or without walking aid (5). Patients' gait score ranged from 2 to 5. A detailed summary of the patients can be found in Table 1.

We gave patients an iPhone and asked them to insert it into a pocket and walk around the hospital. We did not give any

#	Gender	Age	Walking Style	Gait Score
P1	F	77	crutches	2
P2	F	70	crutches	4
P3	F	47	crutches	3
P4	М	68	crutches	4
P5	F	44	crutches	4
P6	М	86	crutches	5
P7	F	66	crutches	3
P8	F	59	normal	5
P9	F	68	normal	5
P10	F	72	normal	5
P11	F	69	normal	5
P12	М	79	normal	5

**Table 1:** Data about participants of our experiment including walking style (crutches / normal) and gait score (0-5).

instruction as to where or how to place the iPhone. Patients inserted the phone in a pocket of different garments: pants (8), robe (3), sweater (1). Patients oriented the iPhone differently (upwards, downwards) in their pockets. After the walking session, a physiotherapist provided a gait score for each patient.

The iPhone recorded motion data at 100 Hz. We collected an average of 8 minutes per patient. In order to exclude the data recorded by the iPhone while patients inserted or took the iPhone out of their pocket, we removed the first and last 10 seconds of each recording.

#### Results

We measured the accuracy, precision and recall of different supervised classification models at classifying 1) walking style into *walking without walking aid* and *walking with crutches* and 2) gait score. The first classification was done on the entire data set and the second classification was  
 Table 2: Performance of different classifiers at classifying walking style into walking without walking aid and walking with crutches.

Model	Accuracy	Precision	Recall
K-Nearest Neighbors	90,0%	83,1%	74,0%
SVN	92,7%	79,9%	94,4%
Quadratic	02 20/	91,7%	75,7%
Discriminant	30,078		
Ensemble	92,1%	85,3%	77,7%

**Table 3:** Performance of different classifiers at predicting a gait

 score from 0 to 5 for patients walking with crutches.

Model	Accuracy	Precision	Recall
K-Nearest Neighbors	99,1%	75,0%	99,5%
SVN	99,1%	75,0%	99,5%
Simple Tree	90,7%	69,1%	89,0%
Complex Tree	93,5%	71,8%	92,1%

performed on the subset of patients who walked using crutches. These results were validated by means of the 10-fold cross validation technique. The results of the four classifiers that performed the best in terms of accuracy are shown in Tables 2 and 3.

#### Discussion

Our results indicate that it is possible to determine whether patients walk normally or with crutches with an accuracy of 93.3% (precision: 91.7%, recall: 75.7%) using a mobile device in the patient's pocket. Furthermore, assuming patients use crutches, our results indicate that a patient's gait score can be determined automatically with an accuracy of 99.1% (precision: 75% recall: 99.5%).

Orthopedists could base their treatment decisions on daily reports generated by HipRApp. These daily reports could

contain the amount of time patients walk daily, the type of walking aid they use and a gait score. These three metrics are according to orthopedists relevant to estimate the patients' rehabilitation progress.

# Conclusion

We introduced HipRApp, an approach to elicit information about the health condition of patients recovering of a hip replacement surgery. What makes HipRApp attractive for rehabilitation after hip surgery is that it only relies on a mobile device, which is carried in a pocket. HipRApp has been validated in an unconstrained environment during conventional physical therapy sessions with patients after hip replacement surgery. The results of our evaluation suggest that HipRApp can accurately classify the kind of walking aid used by patients and determine a gait score that correlates to gait scores provided by physical therapists.

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