Bag-of-steps: Predicting Lower-limb Fracture Rehabilitation Length

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Abstract

Lower-limb fracture surgery is one of the major causes for autonomy loss among aged people. For care institutions, tackling with an optimized rehabilitation process is a key factor as it improves both the patients quality of life and the associated costs of the after surgery process.

This paper presents bag-of-steps, a new methodology to predict the rehabilitation length and discharge date of a patient using insole force sensors and a predictive model based on the bag-of-words technique. The sensors information is used to characterize the patients gait creating a set of step descriptors. This descriptors are later used to define a vocabulary of steps using a clustering method. The vocabulary is used to describe rehabilitation sessions which are finally entered to a classifier that performs the final rehabilitation estimation. The methodology has been tested using real data from patients that underwent surgery after a lower-limb fracture.

Keywords: medical informatics, gait analysis, bag-of-words, support vector machines, clustering, pattern recognition, health

1. Introduction

Hip and lower-limb fractures are some of the most common lesions amongst the elderly population. This kind of injuries produces a high morbidity and mortality [1] due to both the direct impact of the injury and the often fragile health status of elder patients. When patients are not able to recover their pre-injury degree of mobility, they experience a loss of autonomy and a poorer quality of life. In addition, many patients with lower-limb fractures become highly dependent, meaning that they need to be constantly assisted by care givers or need to move into residential care institutions. This situation causes an increase of costs for the health care systems [2, 3]. Given the current ageing of the population, tackling the issues regarding mobility reduction due to hip and lower-limb lesions becomes a key factor for improving the autonomy and quality of life of patients while reducing the associated costs of the after-surgery processes.

Currently, there is no general standard procedure for mobilization after hip and lower-limb fractures independently of the type of fracture, the type of fracture fixation and the patient's physical state. Nevertheless, it is known that an early mobilization is beneficial for the fracture healing and rehabilitation [4]. Another important aspect during the mobility recovery process is the proper weight loading on the affected lower extremity, which needs to be guided by a therapist as inappropriate load might harm the patient [5]. Therefore, qualitative monitoring of the patient's weight distribution is useful to assist therapists and patients during the rehabilitation period. Such monitoring offers the opportunity to assess the recovery of the lesion; in this sense, recent studies show that there exists a correlation between the weight loading pattern of the patient and the speed of rehabilitation [6]. Thus, it is expected that the use of machine learning techniques can facilitate the obtention of such patterns from examples of past rehabilitation processes, allowing the estimation of patient recovery times. This can be useful both at the clinical and at the organizational level. On the one hand, the estimation of the re-

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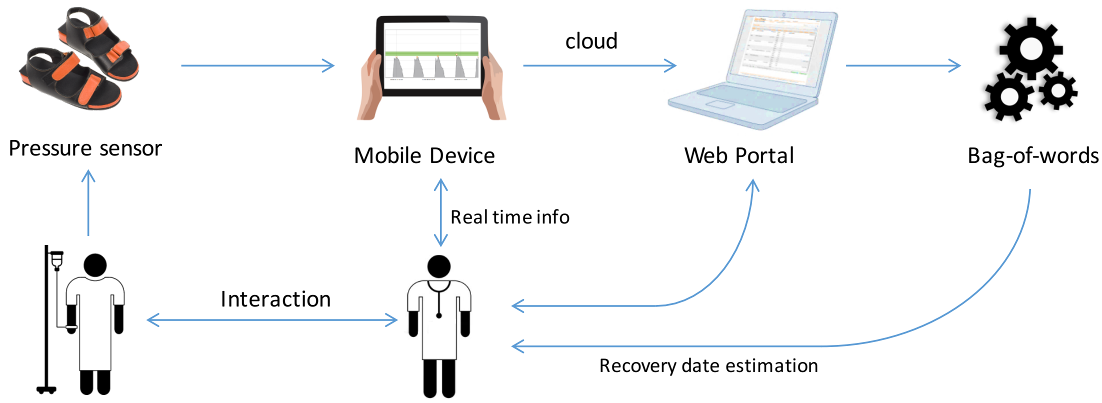

Figure 1: Methodology overview

covery length of a patient will allow therapists to know if the patient is recovering as expected or if the rehabilitation therapy is being effective. On the other hand, having an estimation of patients' rehabilitation length allows hospitals and health institutions to better organize the rehabilitation sessions and to optimize and adapt the hospital resources according to the patients' needs.

In this work we present *Bag-of-steps*: a methodology to learn gait patterns that enables the estimation of the rehabilitation length of elderly patients who suffered an injury or surgery in a lower limb. The methodology, which is based on the bag-of-words pipeline [7], differs from previous works in the fact that *Bag-of-steps* learns the pattern of a set of steps of a patient along a rehabilitation session, instead of focussing in the gait cicle analysis, as previous works do. Our approach proposes to use a triaxial force sensor (*Sensistep* [8]) to gather data of the patients' activity and to analyze it using *Bag-of-Steps* . The sensor registers the force that a patient is exerting on his leg during therapy; next, the gathered information is analyzed using a reasoning engine that, following a bag-of-words pipeline, estimates if the patient is evolving in a proper way and how much time he will need to recover his mobility (see Figure 1). The proposed methodology is tested using real data from patients who suffered a hip or femur lesion and underwent surgery.

This paper is organized as follows: Section 2 presents related work regarding gait analysis and in Section 3 some bag-of-words fundamentals are introduced; Section 4 presents the main contribution of the paper, the *Bag-of-steps* methodology. The methodology is tested in Section 5 using real data. Finally, Section 6 presents our conclusions.

2. Related Work

Despite the problem proposed in this paper still has not been addressed by the research community, gait analysis has been the focus of different studies during recent years . The analysis of the human gait cycle has proven to be a valuable tool for dealing with problems related with the aging of the population such as the treatment of Parkinson [9] or risk of falling evaluation [10]; these works mostly focus on analyzing how the gait cycle is related with the evolution of the diseases and how the gait needs to be represented. In our work we use artificial intelligence techniques to analyze such descriptors in order to help therapists during the rehabilitation process. Similar approaches have proven to be successful for aiding in the treatment of chronic diseases [11] and in veterinary applications [12].

With respect to the use of sensors, as stated in [13], most research on gait analysis relies on the use of multiple devices that often involve the use of wires between sensors and the data gathering platform. The ambulatory device used in this research, however, enhances patient comfort and ease of use as it is a single sensor equipped with wireless technology. Contrary to other work where the gait data are gathered using gyroscopes, accelerometers, magnetometers and force sensors [14, 13, 10], this study uses only a force sensor. According to [6] the different gait characteristics that can be gathered with a single force sensor give enough information to be able to correlate the data to a recovery date.

Regarding the use of artificial intelligence for gait analysis, the research community has been specially focussed on pattern recognition within the gait cycle in order to classify user activities or to detect event. In this sense, artificial neural networks (ANN) [15, 16, 17, 18, 19] and support vector machines (SVM) [17, 11, 19] have been the trend in the gait analysis field. In this paper we follow such trend, but we propose to integrate it to a gait analysis pipeline based in the bag-of-words methodology.

3. Background on bag of words

The bag of words methodology is well known for its usefulness in text and document classification. In it, each piece of text is represented as a set of words belonging to a vocabulary; then, each text is classified using the appearance frequency of each word. This methodology has been broadly adopted in the computer-vision field, where it is mainly used for object and scene recognition [7, 20], but it has also been explored in other domains such as bioinformatics [21] or sound recognition [22].

For the sake of clarity, here we briefly describe the bag-of-words [23] pipeline used in text recognition. Given a set of texts (examples), the bag of words methodology allows to build a document classifier based on the content of the documents. In such a way, future texts can be classified and/or labelled. To that end, the following process is defined:

1. Identify relevant words
2. Define a vocabulary of the most frequent words. Any entry of the vocabulary is called a codeword
3. The occurrence of the codewords inside each document is counted
4. Each document is represented by a codewords histogram
5. A machine learning technique is used to build a classifier using the histograms representing the examples.

In computer vision, the codebook is created by clustering image descriptors of the training data; in such scenario, the centroids of the clusters are used as codewords. The codewords histogram is then build by assigning each descriptor of an image to its nearest centroid.

The bag of words methodology, both in text analysis as well as in computer vision, relies on identifying relevant key-words and analyzing their frequence of appearance rather than in taking into account the word ordering. The problem we are facing presents a similar scenario as, according to therapists [6], the key for rehabilitation is the proper weight loading on the injured leg. In that regard, patients that are close to being rehabilitated are expected to perform steps with a proper weight loading pattern more frequently than those who still need a long therapy.

4. Bag-of-Steps

The bag-of-steps methodology is used to support therapists in their decision making by estimating patients' rehabilitation lenght using data gathered in a rehabilitation session (see Figure 1). In a rehabilitation session, a patient wears an special sandal with a foce sensor that records the weight the patient is bearing on his ijured limb. Data received from the sensor is streamed to a mobile device so the healthcare professional can monitor the weight in real-time and give instructions to the patient based on this information. The measurement data is stored on a mobile device (a tablet or a smartphone) until it obtains Internet connection, then data are sent to a secure database in the cloud. This information can be retrieved through a secure Web Portal. The health care professional can view the measured weight patterns and compare these to those recorded during previous exercises. In order to facilitate comprehension and analysis of the data, and to facilitate the patients' assesment, the bag-of-steps methodology is used.

Bag-of-steps generates a vocabulary of steps and learns a classifier from a set of historical data of patients whose rehabilitation have finished (examples). The bag-of-steps methodology is based on the bag-of-words [23] methodology, with the particularity that we have signals coming from a force sensor as raw data instead of words or images. Therefore, we need to first characterize what our *words* are. To than end, our methodology is composed by the following stages: 1) identify and describe the features that characterise the steps, 2) group steps which share similar characteristics into step stereotypes or *codewords* to define a vocabulary, 3) characterize rehabilitation sessions according to the vocabulary (histograms) and, finally, 4) build a classifier relating the number of stereotypes appearing in a rehabilitation session and the rehabilitation length of the patient (Figure 2). All the stages of *Bag-of-steps* plus the method to recognize stereotype patterns in future patients are described in the remainder of this section.

4.1. Feature identification and step characterization

Once a patient ends a rehabilitation session and the data recorded using the sensors is stored in a server, the available information consists of a large set of continuous data representing the weight put on the injured leg. Thus, first of all data are preprocessed in order to determine which data segments belong to actual steps, according to the following procedure:

1. Noise reduction: the signal recorded by the sensor is smoothed using a Gaussian filter.
2. Step detection: according to therapists' expertise, a data fragment can be considered a step if it satisfies the following conditions:
    - During a period comprised between 0.2 and 2.0 seconds, the weight loading is higher than 10% of the patient's weight.
    - The patient has a loading peak higher than 20% of his weight.

Next, detected steps are described using features determined by the therapists [6]. Such features are commonly used in gait analysis (Figure 3):

- Step length: duration of a step in miliseconds. The step is measured from the instant were the sensor starts noting a force until no force is exerced on it.
- Stride: duration of the whole gait cycle in miliseconds (equivalent to the sum of the right and the left step lengths).
- Loading rate: Speed in which the weight load of the limb is changing during a gait (Kg/s).
- Loading response: the time instant where the foot, in normal conditions, is completely flat and absorbes the full body weight. Corresponds to the maximum force recording in the sensor.
- Peak: The maximum weight (Kg) beared by the leg during the loading response phase.
- Impulse: Corresponds to the integral weight (Kg) beared by the leg during the whole step.

In addition, the step data might be enriched with patient information like sex, weight, age, height and type of fracture, and with information regarding the rehabilitation session in which the step has been recorded (rehabilitation session number, days since the trauma occurred and days since the surgery).

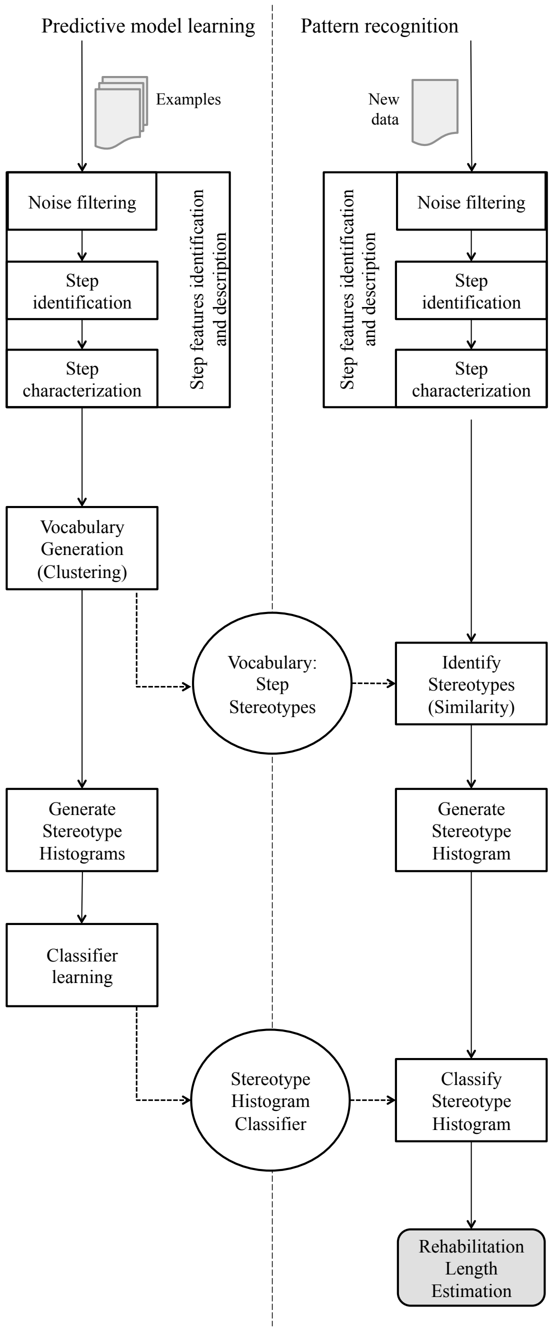

Figure 2: Bag-of-steps methodology schema.

4.2. *Vocabulary Generation: Step Stereotypes*

In the problem we are dealing with, each rehabilitation session is composed by several recordings of steps; thus each step recorded could be considered a word. Nevertheless, contrary to the text analysis domain, it is unlikely to find two steps with the exact same feature descriptors. Therefore, we propose to construct the vocabulary of the *bag-of-steps* in a similar way that is done in computer vision.

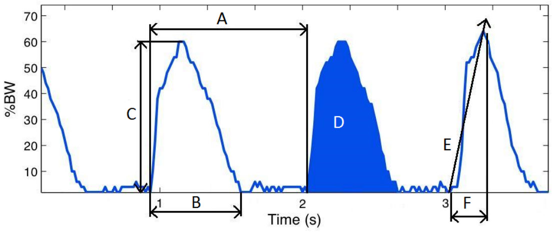

Figure 3: Step characterization features: a) Stride b) Heel stance time c) Gait peak d) Impulse e) Loading rate f) Loading response.

The vocabulary of the *bag-of-steps* can be constructed by clustering all the steps available in the training data and using the centroids of each cluster as the codeword. In such scenario, each centroid represents a step stereotype and we can say that the *bag-of-steps* vocabulary is composed by step stereotypes. The selection of the clustering algorithm and its parameters can have an important influence in the solution of the problem. Given that the step stereotypes will act as histogram bins, an inappropriate number of stereotypes can harm the efficiency of the *bag-of-steps*. A too small number of clusters will result in a low discriminative power whilst too many clusters would result in noise introduction and overtraining. To avoid such issues, we propose to use a parametric method as *K-means* or *K-medoids*, and to define the K value in concordance with the size of the training data (n). This can be done by means of the thumb rule ($\sqrt{n/2}$) or the Rice rule ($2n^{1/3}$). It is important to note that these two rules should be seen as a suggestion rather than as a gold standard as the size of the vocubaulary is highly conditioned by the distribution of the available data; thus, K parameter should be experimentally tuned before proceeding. An example of vocabulary with $K = 20$ is provided in Figure 4.

4.3. Generate Stereotype Histograms

Once the vocabulary is defined, each step of an example is labeled with a particular step stereotype. Therefore, each rehabilitation session can be described as step stereotype histogram of K bins. Figure 5 shows a representation example of a rehabilitation session by using the vocabulary of Figure 4.

4.4. Predictive Model

Once the histograms for the available rehabilitation sessions have been generated, a classifier is trained in order to distinguish between patients with different rehabilitation patterns. Literature offers a great number of classifiers to tackle this stage of the bag-of-words methodology: ANN [24], SVM [25], decision trees and forests [26], etc. In this paper we study the use of 2 different classifiers, nearest neighbour (k-NN) and SVM. Nevertheless, it is important to note that *bag-of-steps* can be implemented with other classifiers. The k-NN classifier is a lazy approach and easy to implement but could perform poorly with no prior knowledge (i.e. feature relevance). k-NN with a $k = 1$ can be considered as one of the simplest classifiers available, and it is useful to establish a baseline for the *bag-of-steps* performance. On the other hand, we opt for support vector machines (SVM) [27] as they offer high generalization performance without the need of *a-priori* knowledge and regardless of the dimensionality of the inputs (which is conditioned by the number of clusters used in the previous step).

4.5. Pattern Recognition

Once a patient performs a new rehabilitation session, his data is analyzed in order to estimate his rehabilitation length. The steps to follow are similar to the ones used to generate the predictive model:

1. The steps performing during the session are identified and characterized following the methodology described in Section 4.1.
2. Each step performed during the rehabilitation session is labeled with a step stereotype from the vocabulary. The labeling is performed by assigning the most similar stereotype to the step. This information is used to build the histogram of the session.
3. The classifier trained in Section 4.4 is used to predict the rehabilitation length of the patient.

It is important to note that, in the sencod step, similarity can be computed according to different distance measures. As a first approach, we use the euclidean distance, and we leave for a future work the exploration of more complex distance measures.

5. Experimentation and results

The methodology presented in this paper has been tested using data containing information of patients who underwent surgery after a lower-limb fracture. Bag-of-steps is tested using different configurations and it is evaluated against other existing methods of the state-of-the-art.

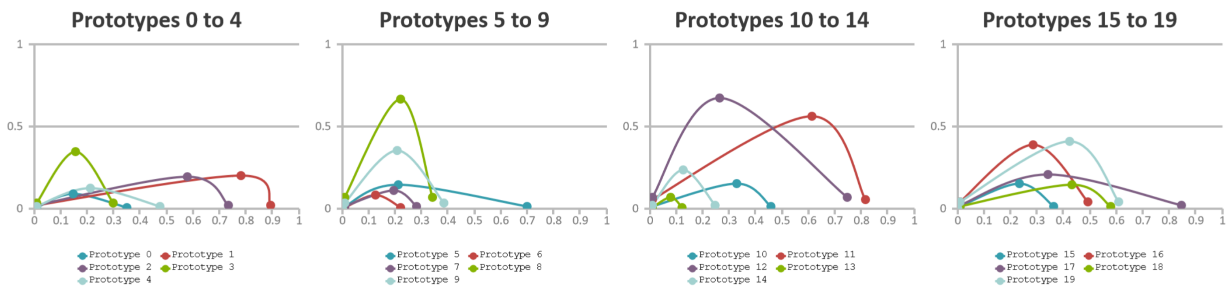

Figure 4: Vocabulary generated for K=20. Steps represented using peak and substride normalized using the patient's weight.

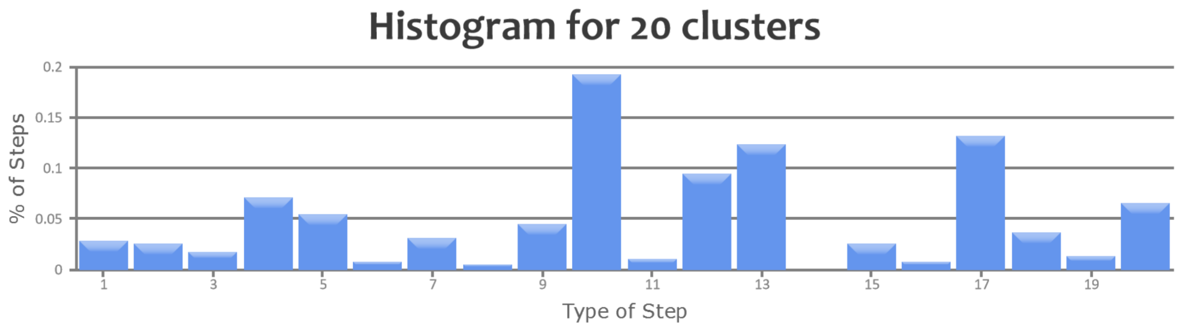

Figure 5: Example represented by an histogram with a vocabulary of 20 stereotypes.

5.1. Data Gathering

Patient data is recorded using the SensiStep technology developed by Evalan. The system consists of a force sensor that is placed inside a special sandal. This sensor registers how much axial force is exerted on the leg [6]. This provides information about the intensity of movement and the amount of weight on the leg. The sensor's data are continuously streamed via Bluetooth Low Energy to a special feedback module. This module compares the actual weight with the patient's target (set by the therapist) and gives immediate feedback to the patient about the appropriate load on the leg.

A total of 48 different rehabilitation sessions have been recorded in a dataset and labelled with their corresponding rehabilitation lengths (the time period between his surgery and his official discharge date). On average, each rehabilitation session was composed of 1200 steps. For the experiments, the data was distinguished between sessions belonging to a patient with a long (more than 56 days) or a short (56 days or less) rehabilitation period. Such threshold between the two classes was defined according to the therapists' expertize. The number of rehabilitation sessions corresponding to each class was balanced (24 long and 24 short).

5.2. Experimental set-up

Experiments have been performed following a stratified 10-fold cross validation methodology. We have built the vocabulary for the tests using K-medoids; to evaluate the influence of the vocabulary size, the experiment has been performed with different K parameter configurations: two corresponding to the thumb rule (K=129), and Rice's rule (K=89), plus other lower and higher values: 20, 50, 150, 200. In the experiments we have implemented *bag-of-steps* using a SVM with a quadratic kernel function[1] and using kNN ($k = 1$).

The presented methodology is compared to two adaptations of other machine learning approaches used to tackle similar problems but over gait descriptor:

- **SVM on gait descriptors:** Previous research has used SVMs to classify patient's activity using gait cycle descriptors[17, 11]. Adpating such research, we have trained a support vector machine to classify the steps executed within a rehabilitation session as *long rehabilitaiton* or *short rehabilitation*. The final label of the rehabilitation session (long

[1] In experimental tuning, the quadratic kernel presented a better performance than the linear and the gaussian radial basis kernels, and a similar performance to a polynomial kernel (order 3).

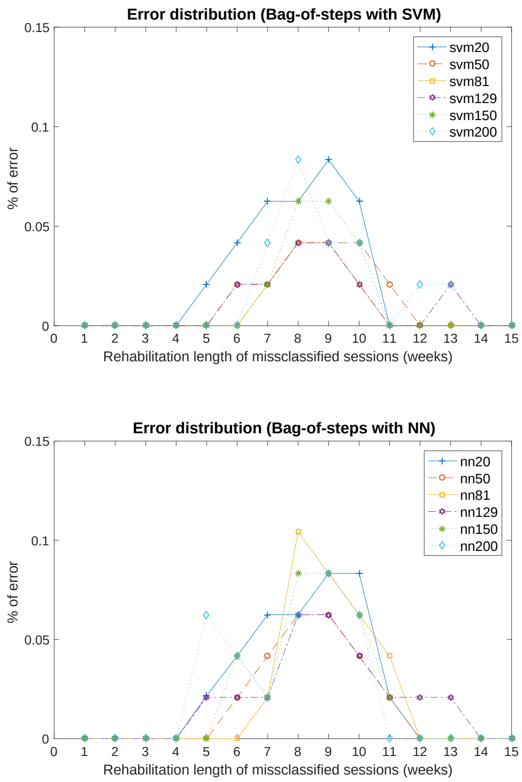

Figure 6: Error distribution along the rehabilitation length of the sessions when using bag-of-steps with a SVM classifer (up) and a NN classifier (down)

or short) is then assigned using a majority voting. This approach can be seen as a partial adaptation of Sama *et Al.*'s work[11].

- **ANN on gait descriptors:**. ANN have also been used for the same purpose[17]. Following an analogous process to the previous one, we have trained an ANN to classify the steps of a rehabilitation session as long or short and we have assigned the final label of the rehabilitation session using a voting schema. The ANN model had an input layer consisting of 6 neurons corresponding to the input gait features, 10 hidden layers and 1 output layer with 2 neurons representing the step types (long or short).

5.3. Results and discussion

The *bag-of-steps* methodology presented satisfactory results (Table 1), obtaining an accuracy of 87.69% in the best configuration (using SVM and the thumb rule for setting K). Nevertheless, the data shows that the size of the vocabulary and the classifier used to build the predictive model have a significant influence on the method performance. If we focus on the classifiers performance, as expected, SVM outperforms kNN with all the tested configurations. It is remarkable that with all the SVM configurations but $K = 20$ and $K = 200$, the accuracy of steps is above the 80%; being 87.69% the best result when using a K value of 81. The best configuration for the kNN classifier ($K = 50$) obtains an accuracy of 77.31%, a quite high value for a classifier that can be considered as the *bag-of-steps* baseline; when comparing this result with the SVM it can be seen that this only improves the results of the worst SVM configurations. A Wilcoxon test ($\alpha = 0.025$) confirms that bag-of-steps obtains better results when using SVM than when using kNN under any configuration but with $K = 50$ and $K = 20$, in which they obtain similar results.

The Wilcoxon test ($\alpha = 0.025$) also points that the best configurations of bag-of-steps (SVM with $K = \{50, 81, 129, 150\}$ and NN with $K = 50$) provide a higher accuracy than the use of SVM or ANN to analyze the rehabilitation sessions using the gait descriptors. This can be explained by the fact that bag-of-steps adopts a broader view of the problem by analyzing the rehabilitation session as a whole, mixing information of all the steps, rather than analyzing the steps one-by-one and then providing a final solution.

When analyzing the influence of the K parameter, the results point that a too small or a too high K value can decrease the performance of *bag-of-steps* as the worst results for each classifier have been obtained when using $K = 20$ and $K = 200$. On the case of NN classifier the best results are obtained with $K = 50$ a whilst when using SVM the best results are when using a K value obtained from the thumbs and the Rice's rule. This fact points that the K value should be carefully tuned according to the classifier used in *bag-of-steps* and that the thumb and the Rice's rule can be useful but are not a silver bullet. It is important to note that the K value will also be conditioned by the heterogeneity of the available data. For instance, experimentation has showed that, in certain cases, slightly higher or lower K values can also provide good results. therefore, we suggest that, when adopting the Bag-of-step methodology, researchers should not limit the vocabulary size to the outputs of the Rice's or the thumb rules. In that regard, we advise using those two techniques as a starting point to experimentally explore the optimal vocabulary size by following a gradient-based approach.

Focussing on the distribution of the error depending

Total Rehabilitation Length: 10-fold Cross Validation						
K	20	50	81	129	150	200
Mean accuracy (SVM)	63.08%	80.00%	**87.69%**	81.53%	80.00%	72.30%
Standard dev. (SVM)	3.94%	5.01%	4.07%	3.78%	3.71%	3.36%
Mean accuracy (NN)	56.92%	77.31%	67.69%	70.77%	69.23%	58.46%
Standard dev. (NN)	3.56%	4.84%	3.14%	3.28%	3.21%	2.71%

Table 1: Accuracy when predicting the total rehabilitation length of a patient when using different classifiers and different vocabulary sizes (K)

Method	Mean	std. dev.
Bag-of-steps (SVM K = 129)	87.69%	4.07%
Bag-of-steps (NN K = 50)	77.31%	4.84%
SVM (Gait descriptors)	72.30%	3.68%
ANN (Gait descriptors)	69.23%	3.14%

Table 2: Comparision of the prediction accuracy between bag-of-steps and other state-of-the-art methods.

on the rehabiliation lenght of the classified cases (Figure 6) we can see that, independently of the bag-of-steps configuration, most of the missclassified rehabilitation sessions belonged to sessions with a duration of 8 or 9 weeks - which corresponds to the threshold of 56 days-. This suggests that the the frontier between a short or a long rehabilitation is a bit fuzzy. It is reasonable to think that training the SVM with a bigger dataset might help to better define such frontier. This behaviour also suggests than a bigger training set might allow the classification of rehabilitation sessions in a more accurate way, increasing the number of classes to be considered in the model, or even to provide a numeric estimate.

6. Conclusions

This paper presented *bag-of-steps*, a methodology for predicting the rehabilitation length and the discharge date of patients who suffered a limb-related surgery and are being rehabilitated. The methodology, uses force sensors which gathers the weight load of the leg of the patient during a rehabilitation session. The recorded data is then analyzed in order to detect the gait of the patient. The gait is then characterized using step descriptors that are compared with other step stereotypes to finally build a step histogram for the rehabilitation session. Using a classifier (SVM or NN), the histogram is then used to estimate the rehabilitation length of the patient.

The methodology has been tested using data from real patients. Preliminary experimentation has shown that *bag-of-steps* can estimate the rehabilitation length as large or short with an accuracy of 87.69% in the best of the configurations tested, outpeforming the results of classifiers typically used in gait analysis. Nevertheless, further experimentation should be carried out in order to determine if the method can also perform more precise predictions, such as the number of days for rehabiltation. To this end, further works include collecting information from more patients as it is expected that by including new data into the model, the predictive power of the methodology will increase. In addition, testing alternative clustering and classification techniques and alternative distance metrics would also be an interesting work to study the flexibility of the presented methodology.

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