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Subsequence Dynamic Time Warping as a Method for Robust Step Segmentation using Gyroscope Signals of Daily Life Activities

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Abstract— **The segmentation of gait signals into single steps is an important basis for objective gait analysis. Only a precise detection of step beginning and end enables the computation of step parameters like step height, variability and duration. A special challenge for the application is the accurateness of such an algorithm when based on signals from daily live activities.**

In this study, gyroscopes were attached laterally to sport shoes to collect gait data. For the automated step segmentation, subsequence Dynamic Time Warping was used. 35 healthy controls and ten patients with Parkinson's disease performed a four times ten meter walk. Furthermore 4 subjects were recorded during different daily life activities. The algorithm enabled counting steps, detecting precisely step beginning and end and rejecting other movements. Results showed a recognition rate of steps during ten meter walk exercises of 97.7% and in daily life activities of 86.7%.

The segmentation procedure can be used for gait analysis from daily life activities and can constitute the basis for computation of precise step parameters. The algorithm is applicable for long-term gait monitoring as well as for analyzing gait abnormalities.

I. Introduction

THE analysis of human activity is a major factor in the clinical diagnosis and during therapy of movement disorders. The detection of single steps is often used as a measure for activity. Common rating tools for activity are often standard pedometers. With these tools only a quantitative measure of the activity is available. Information about fall risk or movement impairments cannot be derived from these quantitative measurements. However, in many cases detailed information about steps is necessary. Therefore an automated recognition and segmentation of single steps is necessary for a detailed calculation of step parameters like step length, step variability, or step time.

Step detection based on wearable sensor systems mostly use accelerometer and gyroscope data. Many algorithms for gait cycle segmentation were based on peak detection methods [1-3]. Selles et al. [1] used two uni-axial accelerometers mounted directly below the knee to detect initial and terminal contact. Their algorithm first computed an approximate stride length, then divided the gait into estimated strides and used a peak detection to locate initial and terminal contact for every stride. Their experiments were done at different walking speeds and considered to be applicable in clinical environments, gait labs, and daily life.

In [2] and [3], an accelerometer was mounted on the hip. The algorithms for step detection were also based on finding minima and maxima after different preprocessing steps like filtering and derivation. In [4], a gait detection algorithm was proposed that worked on signals acquired with an ankle mounted accelerometer. Gait signal was processed sequentially to detect single gait cycles. First, moving and stopping blocks were separated. Second, stance and swing phase were classified during the moving block. Last, the swing phase was searched for positive peaks.

Another approach for step detection was to divide one step into different gait phases [5, 6]. In Sabatini et al. [5], a gyroscope mounted on the foot-instep was used for data collection. Their algorithm assumed that one gait cycle consisted of four gait phases. For each transition between these different gait phases, threshold-based conditions were constructed. Therefore prior knowledge about the single transitions was acquired. In the same research group, Mannini et al. [6] developed an algorithm that used the different gait phases and transitions to train a four-state left-right Hidden Markov Model. Sabatini et al. and Mannini et al. both evaluated their algorithms at different walking speeds and different inclinations using a treadmill.

In [7], a template-based method for step segmentation was described. A step template was computed as the mean value of several steps. The template was compared to the complete gait signal. Using cross-correlation between the template and the signal, the starting points of all steps could be found. The disadvantage of this study was that the step template had a fixed length and was not adapted to different step durations.

In our study, we also used a template based algorithm for step segmentation. In difference to the cross-correlation method, subsequence Dynamic Time Warping was employed. This algorithm allowed the comparison of signals with different length [8]. Gait signals were recorded from a gyroscope, mounted lateral on a sports shoe. Sensors were attached to the left and right shoe and data was recorded during specific exercises and daily life gait.

II. Methodology

A. Sensor platform and setup

An inertial measurement unit produced by Shimmer Research (Dublin, Ireland) [9] was used to acquire kinematic

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data. The Shimmer sensor unit is a wireless platform that can acquire and transmit data in real-time. The Shimmer sensor was very compact, lightweight and enabled using different sensor modules like gyroscopes and accelerometers. For step segmentation, gyroscope data was only used. The sensor platform contained a MSP430F1611 microprocessor running TinyOS with a built-in 500 series MEMS gyroscope (InvenSense, Sunnyvale, CA, USA). The built in gyroscope enabled the measurement of rotation in three axes yaw, pitch and roll and provided a full scale range of ±500 °/sec and a sensitivity of ±2 mV/(°/sec). Data was transmitted wirelessly via Bluetooth radio or logged on local storage to a microSD card. The sampling frequency was adjusted to 50 Hz. An identical shoe model in different sizes was used to provide comparable conditions for data collection. The sensor units were attached laterally to the heel of both shoes (Fig. 1). Data were collected with custom software developed by ASTRUM IT GmbH (Erlangen, Germany).

Figure 1: Sensor shoe setup – sport shoe with attached Shimmer sensor unit for gait analysis.

B. Data collection

The evaluated data in this study was divided into four different groups: 1) template data, 2) test data – healthy subjects, 3) test data – Parkinson patients, and 4) test data – daily life activities.

The data to train the algorithm optimize parameters and test step segmentation (groups 1-3) was collected in the movement disorder unit of the University Hospital Erlangen. Selected subjects (Tab. 1) were part of an ongoing study of sensor based motion analysis in Parkinson's disease [10, 11]. In this study gait data from 200 Parkinson patients and 200 healthy subjects was already collected. Subjects had to give informed consent based on approval from the ethical committee of the University Hospital of Erlangen (Re.-No. 4208). Included subjects were able to walk independently. In order to generate comparable data, subjects underwent a standardized 10-meter walk, where subjects walked 10 meters four times at a comfortable walking speed.

For data evaluation of steps during daily life activities (group 4), special datasets were recorded at the company ASTRUM IT GmbH in Erlangen.

The individual groups' data were collected as follows:

1) *Template data:* For template generation, **25 datasets** were randomly picked from datasets recorded during above mentioned study. Used date originated from healthy subjects and 10-meter walk tests. Table I gives an overview of the subjects, age, and gender.
2) *Test data – healthy subjects:* For development, testing the step segmentation algorithm, optimizing parameters and thresholds, **10 datasets** of healthy subjects from the above mentioned study were picked randomly.
3) *Test data – Parkinson patients:* For evaluation of the step segmentation algorithm in pathological gait sequences, **10 datasets** of Parkinson patients were picked randomly from the above mentioned study. The Hoehn and Yahr Rating Scale (H&Y) and the MDS-Unified Parkinson's Disease Rating Scale (UPDRS) are two commonly used scales to rate symptoms in Parkinson's disease [12] and were assessed within half an hour of gait recordings.
4) *Test data – daily activity:* For the analysis of daily life activities, **4 subjects** were recorded. The subjects were chosen out of different age groups (20-30 years and 50-70 years). For both age groups one male and one female subject was chosen. To support manual annotation of steps during daily activities, a video was recorded synchronously. All activities were performed according to a predefined protocol. Activities were chosen in order to get signals containing different walking patterns (regular straight walking, walking stairs, walking eight shaped circles) and different daily life activities (Sitting, lying, preparing a sandwich, washing dishes, sweeping).

TABLE I
CHARACTERISTICS OF SUBJECTS

Characteristics	Template data	Test data – healthy subjects	Test data – Parkinson patients	Test data – daily activity
Quantity	25	10	10	4
Sex (m:f)	8:17	5:5	5:5	2:2
Age (±SD)	62 (±11)	55 (±9)	61 (±12)	42 (±19)
H&Y (±SD)	-	-	2.1 (±1)	-
UPDRS motor score (±SD)	-	-	12 (±15)	-

C. Gait Phases and Sensor Signals

In the recorded gyroscope data, the angular velocity in the sagittal plane gave information about foot roll over during gait (Fig. 2). The aim in this study was to recognize unique step sequences respectively gait cycles, not to find exact biomechanical reference points like heel strike and toe off. This could be done in a further processing step. In this study signals only from gyroscope sagittal plane were used.

D. Template generation

To generate a step template, the complete data from *template dataset* was used. This dataset included only gait exercises where subjects walked straight on a ten meter track for four times. In this special case, peak detection was used to extract steps. Peak detection is done on the gyroscope data from the sagittal plane (Fig. 2) by searching for local maxima, which corresponded to mid swing and the minima before and after. With this information the gait cycle was defined and all extracted steps were interpolated to 200 samples. This was done to build an averaged step out of 25 datasets and 681 resulting steps (Fig. 3).

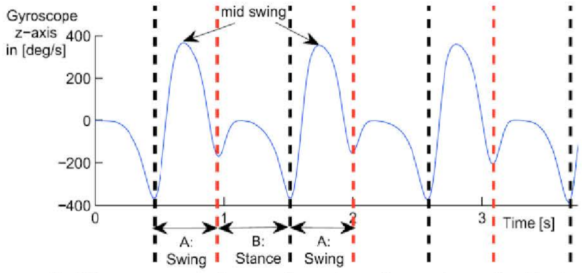

Figure 2: Three consecutive gait cycles of angular velocity in the gyroscope sagittal plane. The red line shows transitions between swing and stance phase and the black line vice versa.

E. Error measurement

To obtain a reliable error value, two different parameters have to be considered. The first parameter is the number of recognized steps from the signal. The aim is to maximize this parameter. However, this leads to the problem that movements, which were no steps but similar, were recognized as steps. Therefore also the number of identical steps (those which were selected manually as well as recognized as steps) has to be maximized. An error parameter, which is the mean value of recognized steps and identical steps, was introduced. This led to a maximum number of correctly detected steps and also to a minimized number of false recognized steps.

F. Subsequence Dynamic Time Warping

Dynamic Time warping is a well-known technique for computing the similarity between two time series. A special form is the subsequence Dynamic Time Warping (subDTW), which allows finding specific subsequences in a long data stream [8].

Inputs for steps segmentation were a reference pattern X (template, Fig. 3, Fig. 4), and a longer data signal Y (Fig. 4), from which the steps were extracted.

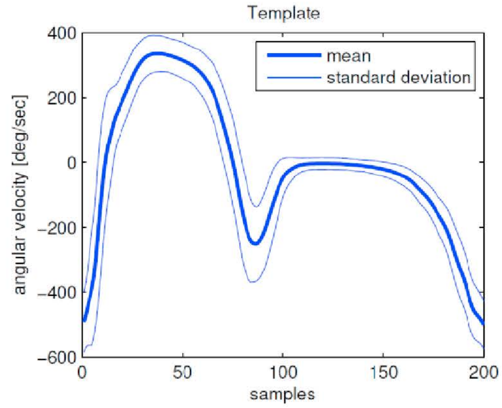

Figure 4: The template was generated by using all 681 steps of 25 subjects. Step signals from gyroscope sagittal plane only were interpolated to 200 samples and averaged.

First, the distance matrix between the data signal Y and the template X was computed (Fig. 4a). Second, the accumulated cost matrix was calculated (Fig. 4c), to simplify the process of finding an optimal warping path [8]. After computing the accumulated cost matrix, a distance function was set up (Fig 4b). The distance functions as well as the end points of three found steps are illustrated in Fig 4b.

When the distance function of found subsequences has a local minimum and is below a fixed threshold t, the found subsequence was identified as a step. The found minimum was identical with the step end point b^*. The cheapest way back from top to bottom, calculated from the accumulated cost matrix, defined the step beginning a^*. For every found step the algorithm checked whether a^* was already used in a neighborhood of another step as b^*, to avoid step overlaps.

The threshold t was estimated by optimizing the reference value introduced in II-E. The dataset *healthy test data* was used to optimize this parameter. All possible thresholds

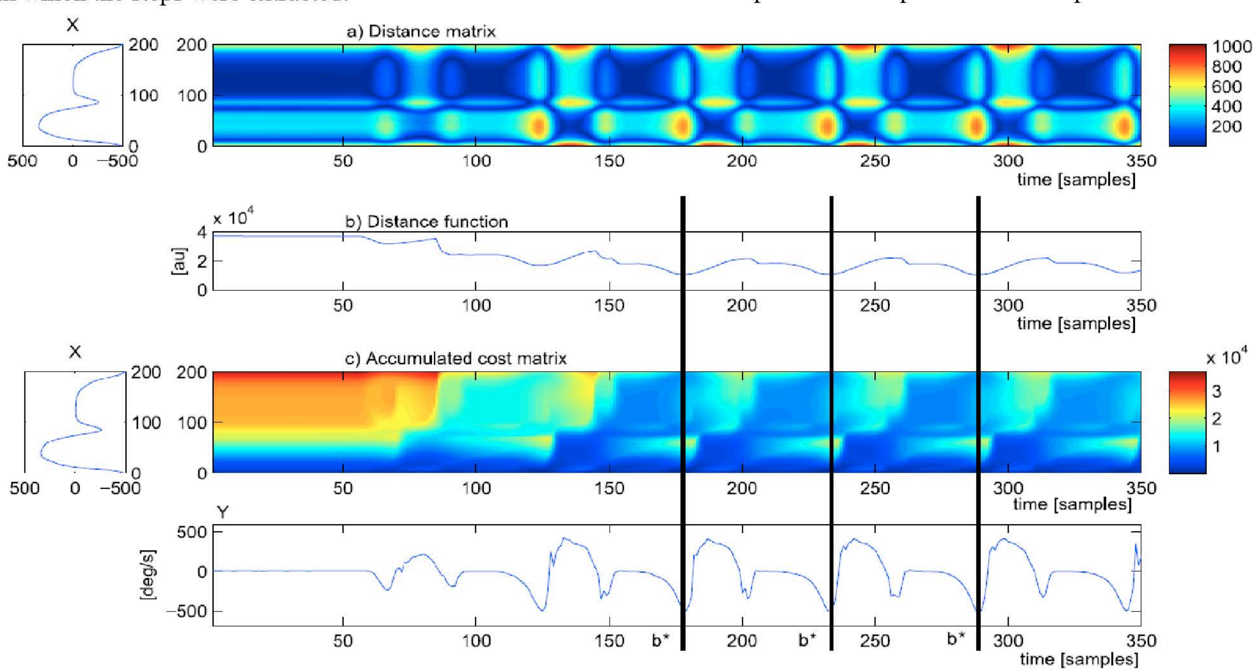

Figure 3: (a) distance matrix between reference pattern X (vertical axis) and gait sequence Y (horizontal axis), (b) distance function, (c) resulting accumulated cost matrix between template X (vertical axis) and gait sequence Y (horizontal axis), black lines indicate the end points b* of the found steps.

within a suitable range were used once for step segmentation. The threshold that yielded the best result with respect to the reference value was chosen as fixed threshold.

G. Step segmentation experiment

To eliminate outliers in the gyroscope signals, a 5 sample median filter was used. Afterwards a Chebyshev type II lowpass filter (cutoff frequency 0.3 Hz, passband ripple 0.5 dB, stopband 20 dB) was used to eliminate noise.

To obtain reliable results for calculating error measures, the step patterns in the gyroscope z-axis of all test data sets were marked manually. For the dataset t*est data – daily activity*, the recorded video was analyzed additionally to control the position of every single step.

III. RESULTS

The number of identical steps described the number of steps that were both segmented by the developed algorithm and marked by hand. Therefore, every manually segmented step beginning and corresponding ending was tested in a local neighborhood of ten samples for an automatically segmented step beginning or ending. If a segmented step was found in this region, this step was declared to be an identical step. Furthermore, the absolute differences between manual segmented starting and end points and automatically segmented starting and end points were calculated. The means of the differences of all identical steps result in the parameters *Start diff* and *End diff*. Results listed in table II.

TABLE II
RESULTS OF STEP SEGMENTATION

	Test data – healthy subjects	Test data – Parkinson patients	Test data – daily activity
Steps (No.)	560	668	1256
Identical steps (No.)	547	504	1092
Identical steps (%)	**97.7**	**75.5**	**86.7**
Start diff (samples)	0.03	0.03	0.03
End diff (samples)	0.36	0.35	0.32

Segmentation results for gyroscope sagittal plane; No.: Number of steps; Start diff, End diff show the mean difference of start and endpoints in samples; threshold was optimized to t =10 for *test data – Healthy* and *test data – Parkinson*, and to t= 20 for *test data – daily activity*.

IV. DISCUSSION

The aim of this study was to develop an algorithm for step segmentation using gyroscopes for daily life activities.

The first experiment was based on the segmentation of gyroscope signals recorded during gait exercises. Results for the healthy test group showed a high rate of detected steps of 97.7 %. However, in the group of Parkinson patients only 75.5 % of steps were recognized correctly. This fact is explained by the gait disorder of the patients. Patients with Parkinson's disease often exhibit small and shuffling gait, characterized by flat foot strikes. This means that the initial contact of the foot is not performed by a heel strike but by a strike of the whole foot. Therefore, the roll over from heel to toe does not exist. This roll over formed the characteristic shape of the gyroscope z-axis signals. Without roll over movement the signal got flatter and did no longer fit to the template very well. To improve the results for subjects with gait impairments, 3D gyroscopes and accelerometers and a multidimensional DTW could be used.

When based on daily life activities, the step segmentation worked with 86.7 % of steps correctly recognized. The algorithm found most of the steps and additionally avoided other movements to be classified as steps. A combination with accelerometers could here also improve the differentiation from other movements. If additional data of the other two axes of the gyroscope were used, turning movements could be differentiated from straight walking.

In summary, the step segmentation algorithm based on DTW worked well for detecting straight steps in different kinds of signals. Gait sequences as well as daily activities could be used to segment steps. Even gait signals of patients with gait disorders could be segmented.

To further improve the algorithm, different templates or even adaptive templates could be used. Another extension of the algorithm could be to detect different gait phases of one step or striking points like heel strike, mid swing or toe off. In a following study also algorithms like [6] should be used to compare our algorithm to existing techniques.

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