Automatic gait characterization for a mobility assistance system

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***Abstract*—This paper addresses gait analysis for a mobility assistance robot designed for the elderly people. Six patients and ten healthy peoples were invited to be part of our first pilot experiment. We designed two experiments so as to firstly detect gait parameters and secondly to identify a change of speed. For the first trial, we compared the temporal-distance parameters of the healthy people and of individuals suffering of mobility problems. The percentages of the gait cycle for duration of stance are higher for people with mobility impairment than for healthy people. In the second experiment, we detected the change in walking speed from the ten healthy peoples. Two different metrics derived from the Kullback-Leibler (KL) divergence and from the Generalized Likelihood Ratio (GLR) were employed for walking change detection. The Receiver Operating Characteristic (ROC) curves show a better performance for the signal obtained with the accelerometer sensor than that obtained with the infrared distance sensor. Nevertheless, the results of our experiments demonstrated that both methodologies (KL and GLR) can be used to detect the change points during walking at high or slow speed.**

***Index Terms*—Gait analysis; Speed change; Mobility assistance; Swing time; Stance time**

I. Introduction

There is a growing interest in developing intelligent mobility aid devices for the elderly people [1]. As is well known, the physical function of people declines with age. Older adults, frequently encounter difficulties performing daily living activities (e.g., walking). They use mobility assistive devices, such as a walker, in order to improve their stability during walking. However, intelligent devices can also provide high levels of care for the elderly. Thus, the objective of our research is the design of a robot for mobility assistance and monitoring system for the users (e.g., elderly people with different disabilities). The robot may be used in different environments (e.g., hospitals, homes, and laboratories).

For the above reasons, the research work addressed in this paper focuses on two main issues: (1) identification of gait temporal-distance parameters with a four-wheeled walker system equipped with two infra-red sensors; (2) detection of walking speed change. These two research questions have been organized around two experimental designs. For the first experiment, the gait temporal-distance parameters such as stance time, swing time and cadence were obtained. These parameters were compared for both populations of users: healthy and individuals mobility impairments (see Table I for characterization).

In the second experiment, we investigate the walking speed change detection, which is a very important element in gait analysis. This can help the robot to understand the users' walking patterns and therefore control the mobility assistance system accordingly. There are several different sensor-based systems which can be used to assess gait information, e.g., video-based motion capture systems [2], [3], pressure sensors systems [4], and force plates [5]. Currently, most of these systems are not portable and generally require patients/users to travel to a laboratory for the experiments. Moreover, the logistics of the existing gait therapy and/or gait analysis systems are further limited by cost, availability of adequate amount of practice, expertise necessary to program and execute trials, and liability. The accelerometer-based gait analysis systems have been proved to be excellent portable systems which can be applied to capture data during walking in daily living environments [6]–[8]. Therefore, we combine a 3-axis accelerometer sensor with the infrared distance sensors in this part. Our system is composed of a four-wheeled walker with two types of sensors (see Fig.1).

In order to detect the change point of signal from the two sensors (infrared and accelerometer), a metric-based method is proposed. This methodology has the advantage of low computation cost and thus is suitable for real-time applications. In our experiment, we investigate two measures (metrics) respectively based on the Kullback-Leibler (KL) divergence and from the Generalized Likelihood Ratio (GLR) .

This paper is organized as follow: Section II explains the experimental setup and data collection. The temporal-distance parameters extraction and proposed metric-based methods are described in section III. The results of experiments are discussed in section IV. Finally, section V, concludes our paper and discusses future directions of our research.

II. Experimental setup

All subjects provided informed consent prior to the experiment. They wore their regular shoes and usual clothing during the measurements.

The experiments are divided into two parts: (1) gait analysis; (2) detection changes in walking speed.

TABLE I
CHARACTERISTICS OF SIX PATIENTS

Patients	1	2	3	4	5	6
Age (years)	77	88	90	97	82	90
Sex (M: Male, F: Female)	F	M	F	F	F	M
Height (cm)	160	167	162	148	155	170
Weight (kg)	61	70	52	59	41	68
User of walker	Yes	Yes	Yes	Yes	Yes	Yes
Medical Conditions	Osteoporosis	Gonarthrosis Parkinsonian Syndrome Pacemaker	Osteoporosis Knees Prosthesis Hypertension	Arthrosis Stroke	Hip Prosthesis Aortic Valvuloplasty	Venous Thrombosis Stroke
MMSE	17/30	27/30	14/30	18/30	22/30	14/30
Falls in the previous year	No	Yes	Yes	Yes	Yes	No

A. First Experiment: Gait analysis

1) Subjects: For the first experiment, six patients were recruited (2 males and 4 females) from our partners hospitals Charles-Foix and Albert Chenevier-Henri Mondor from Paris (France). Table I shows their characteristics. Mean age of patients was 87.3±6.9 years, mean height was 1.6±0.1 m, and mean weight was 58.5±10.7 kg. For comparison with healthy individuals, ten healthy people were also invited to the same experiment (7 males and 3 females). Mean age of healthy participants was 26.7±3.4 years, mean height was 1.7±0.1 m, and mean weight was 66.6±12.9 kg.

2) Protocol: Two infrared distance sensors (Sharp GP2Y0A02YK 20 cm-150 cm) were installed on a four-wheeled walker (pedestrian mobility assistance system). The two sensors were installed at 10 cm of the ground, in order to measure the distance between the walker and each leg. All data was collected at 50Hz. The users were not wearing any kind of sensors.

Subjects were asked to walk straight on a flat floor using the four-wheeled walker at their most comfortable pace. The users walked about 10m.

B. Second Experiment: Detect changes in walking speed

1) Subjects: All of healthy people (seven males and three females) who performed the first experiment participated in this second experiment.

2) Protocol: Each subject was asked to walk thirty steps on a flat floor also using the four-wheeled walker. The first 15-steps were slower and the last 15-steps were faster than the normal walk. When subjects changed the speed, they did not stop, therefore trying to make the walking as natural as possible. Simultaneously, data has been recorded by using two different types of sensors : two infrared distance sensors and one 3-axis (X: lateral, Y: anteroposterior, Z: vertical) accelerometer sensor (Nintendo Wiimote [9]). The infrared distance sensors were installed on the four-wheeled walker (see our First Experiment for more details). The light-weight accelerometer sensor was mounted on the subjects (see Fig.1). In this experiment, the data of infrared distance sensor was collected at 50Hz, and the accelerometer sensor data was sampled at 40Hz.

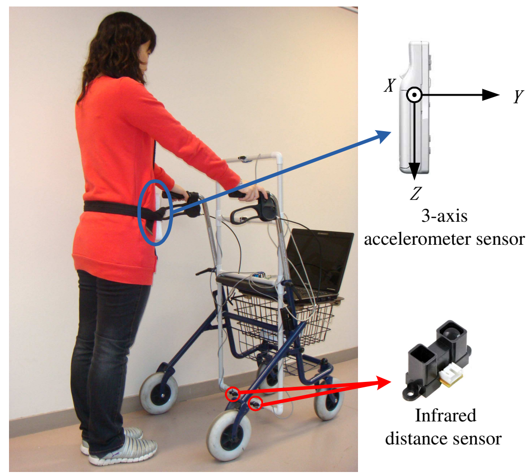


Fig. 1. The placement of two types of sensors

III. ALGORITHM

A. Temporal-distance parameters extraction

The temporal-distance parameters of gait can reflect the information of dynamic activity during human walking. These parameters have been used for gait analysis for many years. In this paper, we extract and analyze some of these parameters such as gait cycle, stance time, swing time, step length, and cadence.

- Gait cycle: The period of time from one event (usually initial contact) of one foot to following occurrence of the same event with the same foot. Each gait cycle consists of the stance and swing phase.
- Stance phase (ST): Begins when the foot makes contact with the ground and ends when the same foot leaves the ground.
- Swing phase (SW): Begins when the foot is no longer in contact with the ground, the foot is free to move.
- Step length: The distance from a point of contact with the ground of one foot to the following occurrence of the same point of contact with the other foot.
- Cadence: the rhythm of a person's walk, expressed in steps per minute.

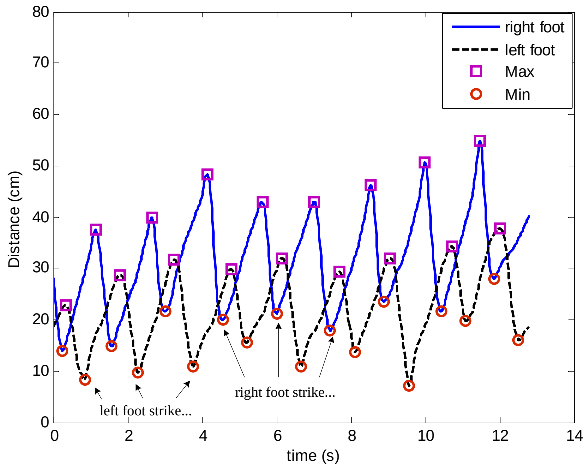


Fig. 2. An example of signal of infrared distance sensor for right foot and left foot (Patient #2)

In order to estimate stance time and swing time, it is necessary to detect the points of foot strike during each cycle. A foot strike is defined as the moment when the foot touches the ground. For our signal of infrared distance sensor, the minimum values correspond the points of foot strike for each foot (see Fig.2). The foot strike indicate the end of a gait cycle or beginning of another gait cycle. Each wave of signal represents a gait cycle. The stance phase can be described here as the period from the minima to the maxima. The swing phase represents the rest part. Therefore, stance time and swing time of one foot (e.g., right foot) can be computed:

$$T_{stance}(n) = t_{max}(n) - t_{min}(n) \tag{1}$$

$$T_{swing}(n) = t_{min}(n+1) - t_{max}(n) \tag{2}$$

where n is the number of gait cycle.

The cadence can be obtained by the number of completed steps and walking time.

B. Walking speed change detection

In this paper, we also attempt to detect changes in speed during human walking. This research can help the mobility assistance robot to understand the users' walking patterns and adapt with them. Walking speed change detection can be investigated as a signal segmentation problem and various schemas can be employed. Indeed, the ultimate goal of segmentation algorithms is to produce sequences with particular characteristics remaining constant within each one [10]. A metric-based segmentation method is applied. Given two adjacent portions (called windows) of signals $X_i = \{x_1, ..., x_N\}$ and $X_j = \{x_N, ..., x_{2N}\}$, this method is to measure a distance (or dissimilarity) value between two windows of the same size. The windows are then shifted by a fixed step along the walking experiment. Many distance measures can be employed. Next, we describe two measures respectively based on the Kullback-Leibler (KL) divergence and on the Generalized Likelihood Ratio (GLR).

1) The Kullback-Leibler divergence: The Kullback-Leibler divergence [11] is an information theoretically motivated measure between two probability distributions. For two distributions P_j and P_j describing two consecutive windows X_i and X_j, the KL divergence is defined as:

$$KL(X_i, X_j) = \int_x P_i(x) \log \frac{P_i(x)}{P_j(x)} dx \tag{3}$$

The divergence is not symmetric and it can therefore be symmetrized by adding the term $KL(X_j, X_i)$ [12]:

$$KL_2(X_i, X_j) = KL(X_i, X_j) + KL(X_j, X_i) \tag{4}$$

When the distributions are modeled using a single Gaussian distribution $\mathcal{N}(\mu, \sigma)$, the symmetric divergence KL_2 can be expressed in a closed form:

$$\begin{aligned} KL_2(X_i, X_j) = & \frac{\sigma_{x_i}^2}{\sigma_{x_j}^2} + \frac{\sigma_{x_j}^2}{\sigma_{x_i}^2} + \\ & + (\mu_{x_i} - \mu_{x_j})^2 \left(\frac{1}{\sigma_{x_i}^2} + \frac{1}{\sigma_{x_j}^2}\right) - 1 \end{aligned} \tag{5}$$

2) The Generalized likelihood Ratio: The second approach employed is the generalized likelihood ratio that measures the distance of likelihood determined from the two hypotheses H_0 and H_1.

- H_0: assumes that the data in both windows has been produced by the same stochastic source ($X = X_i \bigcup X_j \sim \mathcal{N}(\mu, \sigma)$), and in our case, the walking speed is constant.
- H_1: assumes that the data has been produced by different sources ($X_i \sim \mathcal{N}_i(\mu_i, \sigma_i)$ and $X_j \sim \mathcal{N}_j(\mu_j, \sigma_j)$): a change in the gait patterns.

Therefore, based on the two hypotheses, the Generalized Likelihood Ratio (GLR) is determined from the formula [13]:

$$GLR(X_i, X_j) = \frac{L(X, \mathcal{N}(\mu, \sigma))}{L(X_i, \mathcal{N}_i(\mu_i, \sigma_i)) L(X_j, \mathcal{N}_j(\mu_j, \sigma_j))} \tag{6}$$

The distance is obtained by taking the negative logarithm of the likelihood ratio:

$$D(X_i, X_j) = -log(GLR(X_i, X_j)) \tag{7}$$

3) Gait change detection: Each signal was firstly divided in equal size windows (2s) and thereafter the dissimilarity value between the two adjacent windows was computed (see Fig.3). Since the length of windows could influence the result of detection, we defined an adaptive window size. In our search, the length of windows was given according to the average of the gait cycle time of all subjects. The windows were then slid by steps of 0.2s in order to obtain the desired metrics.

For both approaches described in sections III-B1 and III-B2, a high distance value indicates a possible gait change and a low value shows that two portions of signal correspond to the

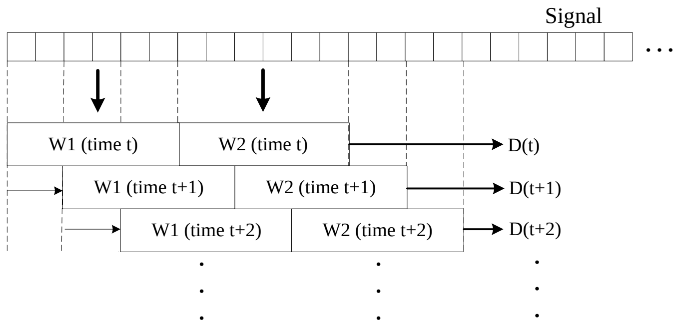


Fig. 3. Distance computation

same gait conditions. According to Delacourt et al. [10], a local maximum of distance is regarded significant if

$$\begin{cases} |D(max) - D(min_r)| > \alpha\sigma \\ \\ |D(max) - D(min_l)| > \alpha\sigma \end{cases}$$

where α is real, $D(min_r)$ and $D(min_l)$ are the right and left minima around the local maximum $D(max)$, and σ is the standard deviation .

IV. Results and discussions

A. Gait analysis

The foot strike points of right and left foot are detected by the minimum values of signal of infrared distance sensor (see section III-A). If we know the foot strike points, the stance time, swing time, and cadence of six patients could be computed. The values summerized in Tab.II represent the mean of each individual suffering of mobility problems during the experiments. The percentage of the gait cycle are shown in parentheses. The mean values for healthy people were also calculated : stance time (0.89 s, 64%), swing time (0.49 s, 36%) and cadence (90.9 steps/min).

We compare the temporal-distance parameters of the healthy people and the six patients. The percentages of the gait cycle for duration of stance are higher for patient than for healthy people. For five of six patients, they have longer duration of stance and slower rhythm of walking than the healthy people.

Figure 4 shows patient #2 using the walker system.

TABLE II
Temporal-distance parameters of each patient

Patients	1	2	3	4	5	6
Stance time (s)	1.09 (68%)	1.03 (70%)	0.55 (65%)	1.84 (78%)	1.31 (67%)	1.12 (68%)
Swing time (s)	0.52 (32%)	0.43 (30%)	0.30 (35%)	0.53 (22%)	0.65 (33%)	0.53 (32%)
Cadence (steps/min)	74.7	83.5	142.8	50.7	61.2	72.1

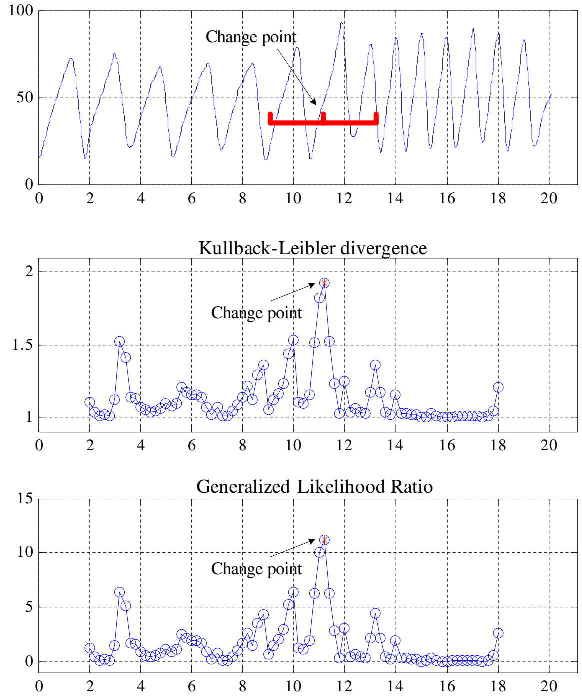
Fig. 4. Patient #2 using the walker system

B. Validation of walking speed detection

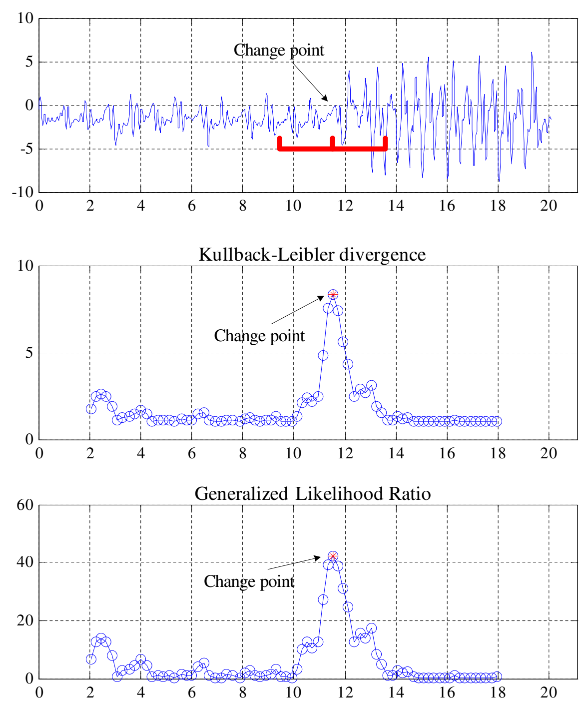
Two examples of two signals from the infrared distance sensor and the accelerometer sensor, respectively are illustrated in Fig.5. The two metrics derived from the KL divergence and the GLR were applied for the two signals. As previously mentioned, a high value of metric corresponded to a possible change in gait pattern, and therefore all local maxima were searched. A local maximum is regarded as a change point when the differences between its value and those of the minima surrounding it are above a certain threshold, and when there is no higher local maximum in its vicinity [10]. Therefore, the change points of signals from two types of sensors were found (see Fig.5).

The walking speed change detection can be regarded as a binary classification problem. Thus, we have different decisions: true positive (TP), true negative (TN), false positive (FP) and false negative (FN). If the change point was correctly classified, the point was regarded as true positive. The sensitivity and specificity are estimated according to the decisions : $senstivity = TP/(TP + FN)$ and $specificity = TN/(TN + FP)$. The tradeoff at different thresholds between the True Positive Rate ($TPR = sentivity$) and the False Positive Rate ($FPR = 1 - specificity$) is visualized in a Receiver Operating Characteristic (ROC) curve by plotting the tradeoff for every possible threshold [14]. The ROC curve was used to visualize the performances of different systems (see Fig.6).

In addition, we measured the accuracy of our systems by the area under the ROC curve (AUC). For the KL divergence based system, the values of AUC for the infrared distance and the accelerometer signals are 0.909 and 0.949, respectively. Concerning the GLR based system, the value of AUC is 0.911 for infrared distance signal and 0.949 for accelerometer signal. These values of AUC reflected that the change point detection of accelerometer signal outperformed that of infrared distance signal by using both metric-based methods (KL divergence and GLR). This result can be explained by the higher amplitude variation of the accelerometer signal, when people changed their walking speed. In addition, the infrared sensor measured the distance between the walker and foot in horizontal direction. However, the vertical locomotion of foot also occurred during human walking. As a result, the infrared sensors could not guarantee the same measurement point of foot during experiments. Generally, the metric derived from the KL divergence is employed to detect the change point during walking at high speed and that from the GLR is used for change detection during slow speed walking. Anyhow, for both of them, the values of AUC are similar in our experiments.

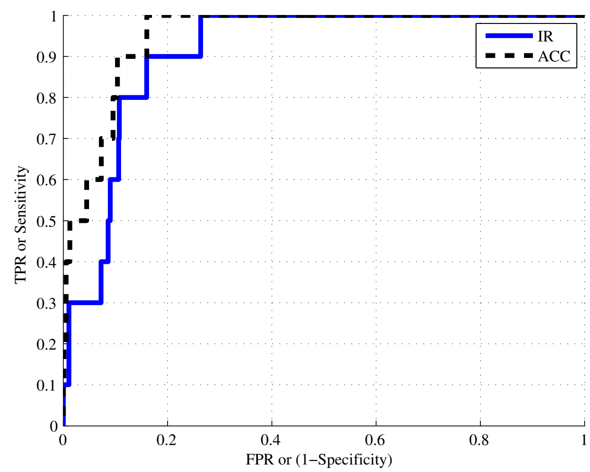


(a)

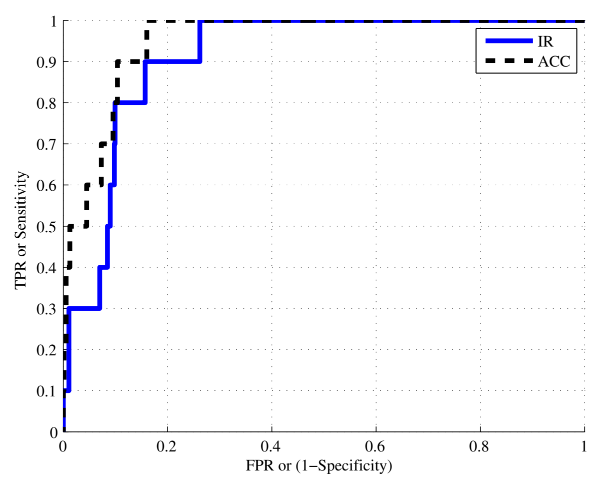


(b)

Fig. 5. Examples of two signals: (a) infrared distance sensor (b) accelerometer sensor (z: vertical).



(a)



(b)

Fig. 6. (a) ROC curves for the KL divergence (b) ROC curves for the GLR

V. Conclusions

In this paper, we calculate and compare the temporal-distance parameters of the healthy people and patients. The percentages of the gait cycle for duration of stance are higher for patient than for healthy people. For five of six patients, they have longer duration of stance and slower rhythm of walking than the healthy people.

In the second part, a metric-based method have been proposed in order to detect walking speed change from two signals (infrared distance and accelerometer). Two metrics derived from the Kullback-Leibler (KL) divergence and from the Generalized Likelihood Ratio (GLR) were tested. For change points decisions, we required a reference segmentation. We compared the reference segmentation with the walking speed change points detected by the metric-based method. If the latter corresponded the former, we considered that this point was correctly classified. To evaluate the performances of our system, the ROC curve was employed. The results reflected a better performance of the accelerometer signal than that of the infrared distance signal. Furthermore, our experiments showed similar results with the two different metrics (KL divergence and GLR). Nevertheless, both of them can be used to detect the change points when people walked at high or slow speed.

Currently, we install two types of sensors on the four-wheeled walker. The combination of different sensors will be investigated in the near future. We are also planning to integrate the described system in our robotic walker.

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