Detection of postural transitions using trunk-worn inertial and barometric pressure sensor: application to stroke patients

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Abstract- To better understand how rehabilitation therapy of stroke survivors is transferred in patient's daily life, activity monitors exist but require multiple wearable devices and may hinder patient's movements. In this study, the use of a single wearable barometric pressure sensor, placed on the trunk, is investigated as a complementary sensor to inertial sensors for reliably identifying Sit-to-Stand and Stand-to-Sit transitions in daily-life, key components of balance control. The pressure was first converted in altitude and then modeled using a sinusoidal fit. Kinematic features (from the inertial sensor) and altitude features from the model were included after selection in a Logistic Regression-based classifier. Data was collected on 12 stroke patients during a period of 9 hours and involving 345 transitions. A sensitivity of 93.2% and specificity of 89.2% was obtained. The results indicate that the proposed methodology can be used to monitor stroke patients' lifestyle and evaluate the outcomes of rehabilitation.

Barometric pressure, stroke, inertial sensor, activities of daily-living, ADL, classification

1. Introduction

Stroke is the leading cause of physical disability for the elderly in the western world. Stroke survivors undergo a very intensive rehabilitation program to re-gain pre-stroke physical abilities. Throughout the rehabilitation process, the patients are assessed several times using questionnaires and/or motor function tests performed at the hospital. However, despite medical relevance, such occasional evaluations carried out in clinical settings cannot measure objectively the transfer of rehabilitation effect/benefit in patients' everyday life.

A recent study [1] has emphasized that the monitoring in daily life of the of the quantity (number) and quality (e.g. duration) of sit-to-stand and stand-to-sit (STS) transfers provides relevant information for balance control and are indicators of physical recovery after stroke. This study used several accelerometers located on the trunk, thigh, and arms for monitoring the patients. However, a multiple-sensor configuration may require a long setup time, and may hinder the patient during long-term recording.

Several studies [2, 3] were done to identify STS transitions in daily-life using a single inertial sensor placed on the trunk and advanced pattern recognition algorithms using features extracted from kinematic signals (acceleration and angular velocity). However, due to physical disabilities, the dynamics of STS transitions changes, resulting in less reproducible kinematical patterns of physically-impaired patients as compared to control subjects. In terms of pattern recognition algorithm's performance, this translates into a limited accuracy in identifying postural transitions in daily-life on pathologic subjects, despite very good performance on a control population. This performance drop calls for a complementary sensing technique enabling directly measurement of the elevation change, inherent to each STS and less sensitive to the kinematical pattern variability of a postural transition.

The recent advances in MEMS technology have enabled the miniaturization of sensors, including the barometric (or atmospheric) pressure sensor. Barometric pressure provides an estimate of the altitude and is suitable for identifying STS transition on healthy volunteers in controlled conditions [4]. However, in application such as monitoring STS transfers, the pressure sensor operates close to its noise level (1.2 Pa / ~10cm) [5] if the thigh length is considered as the minimum elevation change during a STS transition. Furthermore, there is a number of sources interfering with the change of elevation sensed by a barometric pressure, such as temperature and weather changes, or even sudden air flow.

The scope of this study is therefore to investigate whether wearable barometric pressure sensor placed on the trunk is suitable for complementing inertial sensors in the identification of STS transitions in daily conditions and on a stroke patient population.

2. METHODS

Data collection

The data collection was performed at the rehabilitation center (Kliniken Valens in Valens, Switzerland), on 12 stroke subjects (7 Females and 5 Males / Age=59.6±13.6 y.o / Height = 170.1±9.10 cm / Weight = 73.9±14.1 kg) suffering from post-stroke hemiplegia.

Each patient was equipped with a set of wearable sensors and performed daily-life activities as instructed by the physician, for approximately 45 minutes. These activities were suggested in such a way that flexibility was given on how to perform the desired activities. For instance the activity "Read newspaper" includes several basic activities: a long walk to the relaxing area, picking up the newspaper on the table, sitting down on the couch, reading the newspaper for a short time and flipping the pages. Furthermore, the number and the order of the instructed activities were not scripted before the data collection. The target was to include a set of basic activities of daily-living (ADL): short and long walks, walking up and down the stairs, taking the elevators, lying, and standing and sitting with and without arm movements. During the monitoring trial, each patient was videotaped in order obtain reference data for subsequent signal processing development and validation. This study was approved by the regional ethics committee and each patient signed an informed consent form prior to start collecting the data.

Measurement system

A small wearable module (Physilog® 10D Silver, GaitUP, CH) was placed on the patient at trunk location. For validation purpose, an additional module was placed on thigh during the data collection. The wearable modules were wirelessly synchronized, and recorded to an on-board memory card the signals from the 3D accelerometer and 3D gyroscope at 200Hz, 3D magnetometer at 40Hz, and the barometric pressure at 25 Hz. The precision of the barometric pressure sensor is 1.2 Pa (~10 cm) according to the manufacturer's datasheet [5].

Signal processing

Pre-processing

The signals from the accelerometer, the gyroscope and the pressure sensors were first resampled at the same frequency of 40Hz to allow for faster processing. This frequency is still high enough to extract basic ADL features. Furthermore, the wearable sensors were aligned with the body segments using a calibration procedure based on two defined postures: lying down on a bed and standing upright against a wall.

Detection of candidate transitions and Kinematic feature extraction

In order to identify STS transitions, first the candidate (or potential) transitions were selected based on acceleration and angular velocity of trunk using the method proposed by Salarian at al. [3]. This consisted of thresholding the trunk flexion angle ($\boldsymbol{\theta_{Trunk}}$) estimated from the pitch gyroscope to find the time of transitions ($\mathbf{t_{TR}}$), defined as the time at which $\boldsymbol{\theta_{Trunk}}$ reaches a minimum below the threshold ($\theta_{Threshold}$). As the focus of this study is the STS transfer, the Lie-to-sit and Lie-to-stand transitions were removed automatically using the trunk angle information from the accelerometer [3], and were considered as a set of candidate STS transitions $\boldsymbol{\Omega}_{candidate}$.

For each transition in the class $\boldsymbol{\Omega}_{candidate}$, the norm of the acceleration in the sagittal plane after band-pass filtering [3] was estimated ($\mathbf{\hat{a}_{Sagittal}}$). Then, a set of kinematic features using $\mathbf{\hat{a}_{Sagittal}}$ and $\boldsymbol{\theta_{Trunk}}$ were extracted [3] as described in Figure 1 and Table 1.

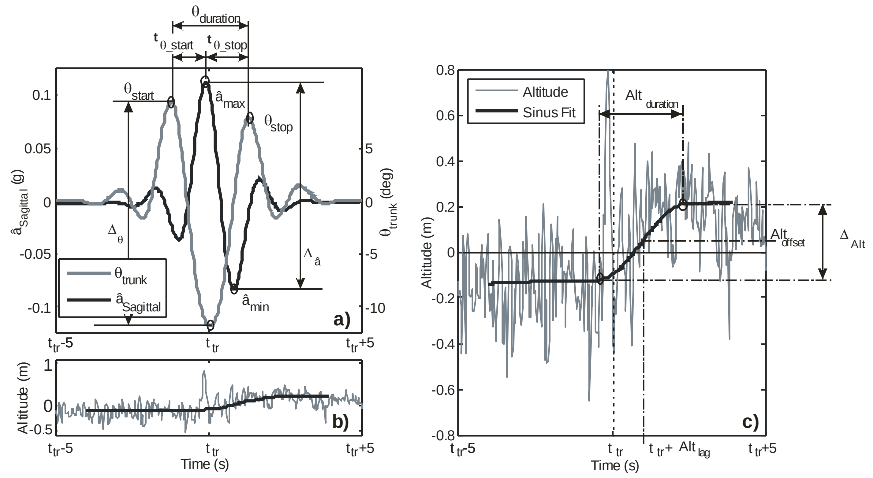

Figure 1. Example of postural transitions. a) Inertial signals after processing and the extracted features. b) Barometric signal (altitude plot) with the correspong sinus fit synchronized with the inertial signals. c) Zoom-in on the altitude plot and the sinus fit with the desciption of the model parameters (except Alt_{drift}).

Table 1. The list of defined features computed in the vicinity of the transition time

Accelerometer features		**Gyroscope features**		**Altitude features**	
Name	*Definition*	*Name*	*Definition*	*Name*	*Definition*
$\Delta_{\hat{a}}$	Range of $\hat{\mathbf{a}}_{\mathbf{Sagittal}}$	Δ_{θ}	Range of $\boldsymbol{\theta}_{\mathbf{Trunk}}$	Δ_{Alt}	Elevation change during transition
$\hat{a}_{max}$	Maximum of $\hat{\mathbf{a}}_{\mathbf{Sagittal}}$	θ_{max}	Maximum of $\boldsymbol{\theta}_{\mathbf{Trunk}}$	Alt_{offset}	Offset from mean value around t_{TR}
$t_{\hat{a}\_max}$	Time of $\hat{a}_{max}$	t_{θ_max}	Time of θ_{max}	Alt_{delay}	Delay from the center of the fit to t_{TR}
$\hat{a}_{min}$	Minimum of $\hat{\mathbf{a}}_{\mathbf{Sagittal}}$	θ_{min}	Minimum of $\boldsymbol{\theta}_{\mathbf{Trunk}}$	$Alt_{duration}$	Duration computed from the Alt
$t_{\hat{a}\_min}$	Time of $\hat{a}_{min}$	t_{θ_min}	Time of θ_{min}	Alt_{drift}	Local drift of the altitude
		t_{θ_start}	Start of transition	$Sign_{\Delta\_Alt}$	Sign of Δ_{Alt}
		t_{θ_stop}	Stop of transition	$\lvert\Delta_{Alt}\rvert$	Absolute value of Δ_{Alt}
		$\theta_{duration}$	t_{θ_stop} - t_{θ_start}	$\lvert\Delta_{Alt}\rvert_{norm}$	$\lvert\Delta_{Alt}\rvert$ normalized by patient's height

Altitude feature extraction

Estimating the elevation change during a transition is of key interest for distinguishing a true (actual) STS transition from a non-transition. Furthermore, temporal features such as the duration of the transition are also of primary interested for clinical purposes [6]. Temporal and amplitude features from the pressure measurements were however more difficult to extract due to the low signal-to-noise ratio and the influences of external perturbations on the sensor to as indicated in the introduction. As a consequence, a sinusoidal fit of the altitude (S), converted from pressure using the barometric formula [7] was modeled as follow:

$$S(t) = \Delta_{Alt} * E\left(\frac{t-Alt_{delay}}{Alt_{duration}}\right) + Alt_{drift} * t + Alt_{offset} \; with \; E(t) \begin{cases} -1/2 & if\ t \le -1/2 \\ 1/2 * \sin(t), & if\ -1/2 < t \le 1/2 \\ +1/2 & t > 1/2 \end{cases} \quad (1)$$

The model included parameters, described in Table 1, to smoothen the signal (e.g. Δ_{Alt}, $Alt_{duration}$) and also to account for specifications of the pressure sensor (e.g. Alt_{drift}, Alt_{delay}). The model was fitted to the altitude data using the "Trust-region reflective" optimization algorithm which enables the parameters to remain within predefined boundaries. Furthermore, $|\Delta_{Alt}|$, the absolute value of the elevation change and its normalized value by patient's height ($|\Delta_{Alt}|_{norm}$) were added to the features set with $Sign_{\Delta\_Alt}$ the sign of the amplitude.

Classification

The Logistic Regression was used to compute the probability (P_{tr}) of a transition in $\boldsymbol{\Omega}_{candidate}$ to be a true transition. In order to avoid over fitting of the parameters, the features were selected using a forward selection algorithm applied on the full dataset $\boldsymbol{\Omega}_{candidate}$. The root mean squared error between the expected value (0 for a non-transition and 1 for a transition) and the probability predicted by the logistic regression was used as a minimization parameter. The selection algorithm stopped when the error did not decrease by 0.5%.

The Logistic Regression model was then trained on the training set as defined in the Validation section, with and without including altitude features. Transitions in the testing set are classified based on the P_{tr} as predicted from the model into two subsets: $\boldsymbol{\Omega}_{predict/True}=\{\boldsymbol{\Omega}_{candidate} / P_{tr} \ge 0.5\}$ and $\boldsymbol{\Omega}_{predict/False}=\{\boldsymbol{\Omega}_{candidate} / P_{tr} < 0.5\}$. Algorithms were implemented in Matlab 2013b (Mathworks, USA).

Validation procedure

During the data collection, the patient was equipped with a wearable module placed on the right thigh. The thigh angle, extracted from the accelerometer signals was first filtered and thresholded to preselect the reference transitions in accordance with Paraschiv-Ionescu et al. [8]. Each of these transitions were then confirmed with the video to form the reference dataset $\boldsymbol{\Omega}_{Ref}$.

A detected transition was defined as a true transition if its time occurrence lies within ±2 seconds of an event in $\boldsymbol{\Omega}_{Ref}$. The dataset $\boldsymbol{\Omega}_{candidate}$ was hence split into two subsets: $\boldsymbol{\Omega}_{candidate/True}$, containing the true transitions and $\boldsymbol{\Omega}_{candidate/False}$, containing the non-transitions.

The walking and lying periods were also computed from the trunk inertial sensors [3]. The candidate transitions occurring during long walking periods (>10 steps) –excluding the edges of the periods–and lying periods were excluded from learning and re-integrated as predicted false transitions.

The performance of the classification algorithm was quantified in terms of sensitivity (SEN) and specificity (SPE) metrics using a 10-fold cross-validation procedure.

3. RESULTS

A total of 345 reference transitions (in $\boldsymbol{\Omega}_{Ref}$) were extracted from the 9 hours of recordings collected on the 12 patients. With a threshold for $\boldsymbol{\theta}_{\mathbf{Trunk}}$ set to -3.0 deg, a number of 669 candidate transitions were detected and included in the set $\boldsymbol{\Omega}_{candidate}$.

Three features out of 19 features (both altitude and kinematic) were selected after the forward features selection step, displayed in the order of occurrence during the selection process: $|\Delta_{Alt}|$, $\hat{a}_{max}$, $\theta_{duration}$. After excluding the altitude features, 4 features were selected: $\hat{a}_{max}$, t_{θ_start}, t_{θ_stop}, θ_{min}.

The overall classification sensitivity and specificity after the cross-validation were 93.2% and 89.2%, respectively (confusion matrix shown in Table 2). By excluding the altitude features, the sensitivity was reduced by 6.8% and the specificity decrease by 4.4%.

Table 2. Classification performance : confusion matrices with and without the inclusion of altitude features.

Feature set		***Altitude + Kinematic***		***Only Kinematic***	
$\mathbf{\Omega_{candidate}} \rightarrow$		**True**	**False**	**True**	**False**
$\mathbf{\Omega_{predict}}$	**True**	329	34	305	48
	False	24	282	48	268
		SEN = 93.2%	**SPE = 89.2%**	**SEN = 86.4%**	**SPE = 84.8%**

4. DISCUSSION

This study investigated the use of barometric pressure sensor as complementary information to the inertial sensor signals for identifying Sit-to-Stand and Stand-to-Sit transitions in daily-life. The barometric pressure signal was first converted in altitude and then modeled using a sinusoidal fit. The kinematic features (from the inertial sensor) and the altitude features from the model were included in a Logistic Regression-based classifier.

The improvements in classification performance by including the altitude features demonstrate the importance of barometric pressure for accurately distinguishing actual from non-transitions. Furthermore, the selected features, including both kinematic and altitude features, show the complementarity of these types of sensing technology for transition detection. In addition, the $|\Delta_{Alt}|$ (non-normalized elevation change) was selected instead of $|\Delta_{Alt}|$ (normalized) suggesting that anthropometric parameters may not improve the classification performance.

Another important aspect of the algorithm is the selection of the threshold $\theta_{Threshold}$. This threshold depends on the dynamics of trunk tilt of the patient during a STS transitions, and may depend on many factors such as physical condition and/or age[6]. It shall be selected in such a way that $\Omega_{candidate}$ is largely inclusive and contains all members of Ω_{Ref} (high sensitivity).

5. CONCLUSION

The results of this study demonstrates that a sensor fusion approach based on combination of barometric pressure and inertial sensors into a single device located on the trunk is a promising configuration (reliable, not-cumbersome) for long-term daily-life monitoring of post-stroke patients. The devised algorithm for signal processing and analysis uses the multi-sensor information in an efficient way as illustrated by the very good performance metrics (sensitivity, specificity). A possible extension of this work is the validation on an extended number of stroke patients and/or patients with other clinical conditions.

6. ACKNOWLEDGMENT

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