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Motion-Logger: An Attitude and Motion Sensing System

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Abstract— **This paper proposes a complete motion sensing solution for wheelchairs with the main objective of determining tips, falls and other hazardous situations. This kind of motion-logging solution is necessary to study needs and habits of wheelchair users. The system collects motion information utilizing an inertial measurement unit (IMU) consisting of three orthogonal accelerometers and two gyroscopes sensing pitch and roll rate. The IMU is part of a portable device (the "Motion Logger") which captures raw motion data in a Secure Digital memory card. An algorithm running in the Motion Logger helps reducing energy consumption and memory usage. Actual determination of major events is carried out off-line and in batch mode using a personal computer application, which has two key components: an attitude estimation algorithm and the event identification itself. This document describes the design process, the hardware, and the main algorithms employed in the motion sensing solution, as well as results obtained with it.**

I. Introduction

This paper describes the implementation of a motion sensing system for determining wheelchair-related falls as part of a major research study carried out at the research center of the James A. Haley VA Hospital (Tampa, Florida). The focus of the study aims at achieving a thorough understanding of the demographics, nature, consequences, and the creation of prediction models of fall events among veteran wheelchair users [1].

The main goal of the motion system is to successfully estimate the motion variables relevant to the occurrence of falls, tips and similar risky situations [2]. Off-line smoothing techniques allow for optimal estimation of angles in the longitudinal (roll) and lateral (pitch) directions of the wheelchair. Pattern recognition techniques may be applied for determining falls and tips while distinguishing them from false positives, such as the case when the wheelchair tilts for folding or when it is being transported.

The paper is organized as follows. In section II, some projects with a similar nature to this one are described briefly. Section III analyzes the required functionality and design requirements. Section IV explains the proposed solution, including the embedded system design and the signal analysis process. Results analysis is addressed in section V. Finally, conclusions and future work are included in section VI.

II. Related Work

Significant research efforts are being carried out dealing with attitude and position estimation of vehicles and other similar mobile platforms. There was however no solution that satisfied all requirements imposed to the platform described in this paper. In [3], a system was attached to a wheelchair for determining several usage statistics such as distance traveled, localization information, seat position and time spent on the wheelchair. Using wheel rotation measurements, velocity, distance and number of stops were estimated. A GPS board was used to collect navigation information. Seat tilt values were measured using a potentiometer. In [4], an improvement to the previously described system was performed incorporating tilt and pressure sensors for determining inclination and seat occupancy, respectively.

In [5], a laser range finder, a three-axis gyroscope and a pedometer were mounted on a cane to provide position and attitude information to blind people. The laser and gyroscopes provided attitude information while the pedometer measured the user's walking speed. The estimation scheme used a two-layered extended Kalman filter. The first one, based on laser and gyroscopes measurements, estimated the 3-D attitude of the cane. The second filter, integrated corner features extracted from the laser data and linear velocity measurements from the pedometer to estimate the 2-D position of the user.

The HOBO Pendant G Acceleration Data Logger [6] is a commercially available motion-data-logging device that stores measurements from a three-axis accelerometer in a 64 KB EEPROM memory. The information is downloaded to a computer through a USB interface. Then, with the help of software included with the equipment, tilt information is computed and displayed graphically. Due to its limited storage and battery capacity, the HOBO Pendant is only applicable to experiments with short duration of time. Furthermore, gyroscopes, not included in the HOBO pendant, would be necessary to accurately estimate dynamic roll and pitch.

III. Problem Description, Challenges and Requirements

The development of the "Motion Logger" is motivated by the need of a device supporting the study of tips and falls of wheelchair users, specifically war veterans. A logging and estimation system must provide accurate information about the motion and attitude of the wheelchair for the accurate determination of hazardous situations, such that appropriate conclusions can be drawn from the study.

According to researchers associated with the Veteran Affairs research center, the system needed to possess several features not found in any commercial solution. Following requirements were proposed:

- Accurate detection of relevant events as required by the study. No relevant events should be missed. At the same time, "false positives" should be avoided to the greatest extent possible.

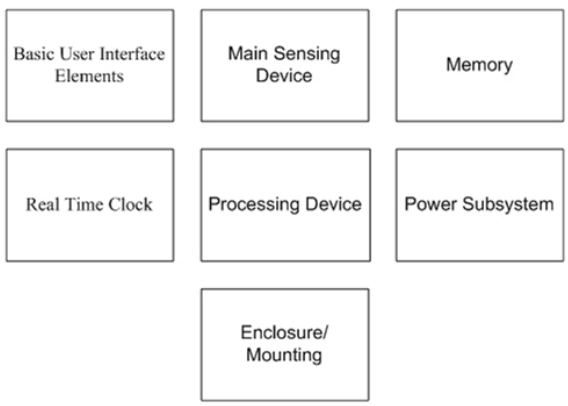

Fig. 1. Embedded application block diagram.

- Unattended operation for relatively long periods of time (˜1 month).
- Adaptability to a variety of wheelchair types and users with minimal intrusiveness to the regular wheelchair operation.
- Robustness and ruggedness.
- Simple use and minimal user interaction.
- Low price.

IV. Proposed Solution

A major design principle followed for devising a solution that fulfilled all requirements, particularly targeting the cost constraints, was to shift as much complexity as possible from the data collection aspect to the data analysis. Personal computers are inexpensive and there are numerous data analysis tools readily available to researchers, such as MATLAB. Hence, the system consisted of two major stages to the proposed solution:

- Data collection, where the main focus is in capturing raw information with high fidelity, while saving power, memory and cost. Here, cost is a key design constraint to be considered, since hundreds of data collection devices (Motion Loggers) would be distributed to many study participants. Another aspect to be careful about is observability, which needs to be guaranteed for the proper estimation of the main magnitudes.
- Data processing. All the intelligence required to successfully indentify relevant events should be placed on this aspect of the technological solution. Having access to raw data also allows for employing different attitude estimation or pattern recognition techniques, and for comparison of different approaches. Thus, there is the possibility for this aspect to evolve. In this specific study, the data analysis stage may be decomposed into two major aspects: Optimal estimation of motion variables from raw measurements, and determination of fall/tip events.

As mentioned before, this system architecture leverages on the computational power of the PC and its large storage capacity. It also allows for minimizing the complexity of the data-logging device, thus reducing its cost.

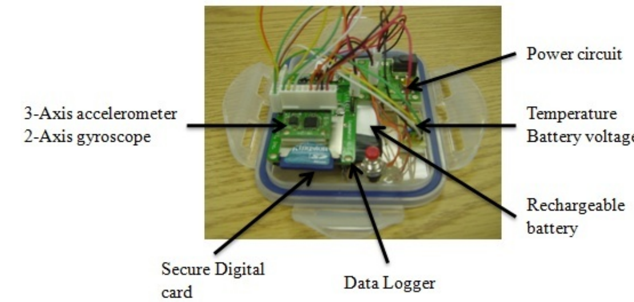

Fig. 2. Embedded device.

A. Data Logging Device

A preliminary functional decomposition of the data logging device yields the block diagram shown in Fig. 1. After a careful evaluation and comparison of several alternatives, a data logging device originally intended for storage of GPS information was chosen for the practical implementation of the initial prototype of the Motion Logger (Sparkfun's Logomatic V1.0 [7]). The Logomatic contains the microcontroller Philips LPC2138, and a Secure Digital card (SD) socket. The SD memory was satisfactory from the point of view of the project requirements due to handling ease for users who do not possess computers. Motion-Logger users would just place the SD card in an envelope and send it to the research center. Shortly before, they receive a fresh SD card for replacement to ensure uninterrupted execution of the study.

The motion sensing function in the data logging device is realized by an Inertial Measurement Unit (IMU) containing 3-axis accelerometers [8] and 2 gyroscopes [9] obtained from the same vendor. In addition, temperature and battery voltage are measured for device characterization and for monitoring power supply behavior with the help of a custom circuit. The device is attached rigidly to the wheelchair in order to capture the motion variables with high fidelity. A picture of the actual embedded system is shown in Fig. 2.

1) Embedded Application: Three-axial acceleration and roll/pitch rate information is processed by an embedded application such that measurements are stored only when the wheelchair moves. This functionality is essential for saving storage space and energy. Code for the custom embedded application was written using some functions of the Logomatic's firmware, whose source code was also provided by the vendor.

The customized embedded application incorporates following features:

- Real time multichannel signal processing for selective data storage.
- Time-stamping.
- Reading input elements for user interaction.
- Battery and temperature monitoring.

The signal processing algorithm is based on a high-pass digital filter applied to each sensor output. The output of the digital filter determines when a relevant change has occurred then triggering the memory writing process. Digital filter design is straightforward. It was determined experimentally that relevant frequency components for most wheelchair users are below 10 Hz. Based on that, the sampling rate was set to 20 samples/sec. To eliminate the DC component (offset) and slow changes in sensor bias, the corner frequency of the high pass filter was set to 2Hz. It should be emphasized at this point that the sensor information is processed only for determining when to trigger the writing process on the SD card; nevertheless data from all sensors is stored in raw form.

Repeated experiments verified that the system was sensitive enough to detect vibrations and any kind of motion, but avoided storing data when the wheelchair was static. This simple solution allowed for balancing two conflicting requirements, namely sensitivity vs. storage/energy efficiency. The basic algorithm is presented graphically in simplified form in Fig. 3. To make sure that the system does not discard relevant data, a circular buffer is maintained so that any time change is detected in any of the sensors, the system stores data half of a second before the occurrence of the event. Data continues to be stored while motion is detected and it stops 5 seconds after any activity period. The real time clock module of the processor is used to generate a time-stamp whenever a new event is detected. A sample of one of the frames generated by the embedded application is shown in Fig. 4. The first line of the frame contains, from left to right, the digitally converted values of temperature, measured by an LM35 temperature sensor, a fraction of the source voltage, a reference voltage from a precision voltage reference IC (LM4041) with a constant output of 1.225 Volts, and the time when motion was detected. All converted values are in the range 0-1023 since the ADC module uses 10 bits for the conversion process of the analog signals. After the first line, which is included every time a new event is detected, the digitized sensor outputs are stored in the SD in the following order: roll rate, pitch rate, vertical acceleration, lateral acceleration, longitudinal acceleration.

The final action taken towards the goal of reducing energy consumption was to reduce the clock frequency. A change from 60 MHz to 30 MHz produces a reduction of average current draw from 70mA to 30mA. This current component is only due to the microcontroller operation and processing algorithms, but does not include the memory writing process. The SD memory writing procedure generates an additional current burst between 12 and 18 mA, as verified through oscilloscope measurements. A commercial-off-the-shelf (COTS) rechargeable battery system is used as the source of energy for the embedded application. It comprises a Polymer Lithium Ion battery [10] and a charging circuit [11] for this particular battery chemistry, which is fed by an AC wall adapter. Users are encouraged to charge the Motion Logger every evening or whenever they are not using the wheelchair for a prolonged period of time. As estimated from the battery capacity (2 AHr), as well as experimentally, users can use the Motion Logger for up to 2 days without the need to recharge.

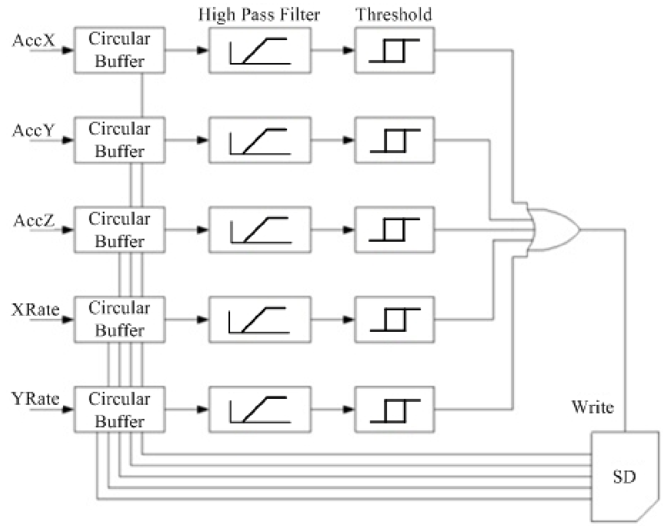

Fig. 3. Real-time signal processing algorithm for selective data storage.

B. Estimation of Motion Variables

1) Calibration Procedure: The calibration procedure involves determining offsets and scaling factors for each sensor. To achieve this, the Motion Logger is subjected to test in six positions, such that the gravity vector is aligned with each accelerometer axis in the positive and negative directions. Using the known gravity acceleration value, scale values for the IMU can be accurately determined. After the calibration process, the estimation algorithm takes into account variability of the sensors, such that accuracy can be improved.

2) Estimation Procedure: As pointed out before, raw sensor data is stored in the SD memory for approximately one month. The first approach for estimating roll and pitch angles is based only on accelerometer information. Hence, it is assumed that the wheelchair is static. Since gravity is always sensed by the accelerometers, it is possible to calculate trigonometrically the two angles under study. Fig. 5 and equations 1 and 2 illustrate the geometric and mathematical relationships that allow for determining these angles. With this simple implementation, which does not incorporate gyroscopic measurements, the results obtained are very inaccurate, since they consider acceleration measurements as the sole effect of tilt, disregarding the acceleration of the platform itself.

$$\phi = \arctan\left(\frac{\tilde{a_y}}{\tilde{a_z}}\right) \tag{1}$$

$$\theta = \arctan\left(\frac{\tilde{a_x}}{\tilde{a_z}}\right) \tag{2}$$

ϕ is roll, θ is pitch, $\tilde{a_x}$, $\tilde{a_y}$, $\tilde{a_z}$ are the measured accelerations in the longitudinal, lateral, and vertical travel directions, respectively. Due to the fact that the device cannot be placed at the perfect center of gravity of the wheelchair, every time the user rotates around the vertical axis, an increment in the Y axis acceleration appears. This is erroneously interpreted as a rotation around the travel direction axis

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T-68-736-379 1/16/2008 11:0:0T
407     508     579     526     495
406     509     593     524     508
405     509     592     524     509
406     509     592     524     509
406     509     594     524     508
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Fig. 4. Sample logged frame.

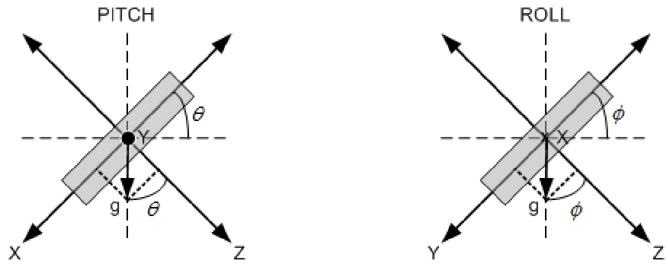

Fig. 5. Gravity components when wheelchair is tilted.

(roll). Additionally, every time the wheelchair starts moving, a false inclination value is obtained due to the large change produced in the accelerometer output. An improved analysis approach implies using the gyroscope measurements. For actual sensor fusion, a linear optimal smoother [12], [13] is employed to estimate roll and pitch angles. Due to the large quantity of raw data to be analyzed (approximately 0.5 GB of data per user for 1 month) important considerations with regard to computational complexity needed to be taken into account. Hence, a simple and efficient variant of the smoother was implemented. The equations shown below describe the system model and measurement model for the smoother:

$$x_{k+1} = \Phi x_k + R \tag{3}$$

$$z_k = C x_k + Q \tag{4}$$

- x_{k+1}: Next state value calculated from the model.
- x_k: Last estimated value for the state.
- Φ: State transition model matrix.
- C: Measurement model matrix.
- z_k: Measurements.
- R: Model error covariance matrix.
- Q: Measurement error covariance matrix.

The state of the system, x, is shown below:

$$x = \begin{bmatrix} \phi \\ \theta \\ p \\ q \end{bmatrix} \tag{5}$$

- ϕ: Roll angle.
- θ: Pitch angle.
- p: Angular rate in the longitudinal direction.
- q: Angular rate in the lateral direction.

It is assumed that pitch and roll angles are measured, even though they are being calculated from acceleration measurements. The state transition model matrix and the measurement model matrix are shown below:

$$\Phi = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{7}$$

where T_s is the sampling time (50 msec). The smoother itself, known as Rauch-Tung-Striebel algorithm, is basically a filtering algorithm run in two directions: forward and backward [13]. The forward filtering follows the Kalman filter equations, which are well known and straightforward to implement [12]. During the Kalman filtering process, all a priori $\hat{x}_{k+1/k}$ and a posteriori $\hat{x}_{k/k}$ computed state estimates need to be saved along with their covariance matrices, that is $P_{k+1/k}$ and $P_{k/k}$, respectively. The smoothing gain is given by

$$A_k = P_{k/k} \Phi^T P_{k+1/k}^{-1} \tag{8}$$

A_k is used to obtain the smoothed estimates from following relationship:

$$\hat{x}_{k/N} = \hat{x}_{k/k} + A_k \left(\hat{x}_{k+1/N} - \hat{x}_{k+1/k} \right) \tag{9}$$

Here, $\hat{x}_{k/N}$ represents the smoothed estimate, and $\hat{x}_{k+1/N}$ is the previously computed smoothed estimate during the backward filtering process. The covariance matrix of the smoothed estimates may be obtained from the expression below. However, this value is not used in the backward filtering procedure.

$$P_{k/N} = P_{k/k} + A_k \left(P_{k+1/N} - P_{k+1/k} \right) A_k^T \tag{10}$$

C. Fall and Tip Detection

Based on the estimated longitudinal roll and lateral pitch angles, a fall and tip detection algorithm is used to further process the filtered data. The algorithm steps are:

- The algorithm checks that the battery was properly charged at the time the tip or fall was detected, which indicated sensor measurements were reliable.
- At the beginning of each frame, whose length depends on the activity intensity of the user after the start of motion, the software checks that the first estimated angles do not contain high values. This assists in the avoidance of false positives associated with events when the wheelchair is stationary and tilted without the user sitting on it.
- If any of the angles are higher than a threshold, during a certain amount of samples, an event is labeled as a likely fall or tip. The thresholds were set to 50 for tips and 150 for falls. The algorithm also checks that the angles do not keep changing polarity for longer than 10 seconds since such pattern is likely to represent the case when the wheelchair is being transported in a vehicle. Regular wheelchair usage is not likely to generate continuous fast tilt changes. A short-time average zero-crossing rate (per sample) is used to estimate the frequency

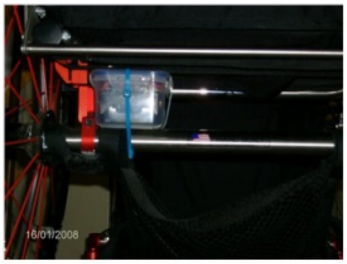

Fig. 6. Device attached to wheelchair.

component of the signal for the given analysis time, and can be measured as follows [14]:

$$Z_n = \frac{1}{2L} \sum_{m=n-L+1}^{n} |sgn(\phi[m]) - sgn(\phi[m-1])| \quad (11)$$

- L: Analysis window length.

The equivalent sinusoidal frequency corresponding to a given zero-crossing rate per sample is [14]:

$$F_e = 0.5 F_s Z^{(1)} \quad (12)$$

- $Z^{(1)}$: Zero-crossing rate per sample.
- F_s: Sampling rate.

- Since a tip or fall event is not likely to contain periodic variations, but rather sudden fluctuations, frames with periodic behavior should not trigger an event detection. The autocorrelation function of a periodic signal is also periodic with the same period [14], and may be used to measure angles periodicity during a short-time window as given below [14]:

$$R_n[k] = \sum_{m=0}^{L-1} \phi[n+m]\phi[n+m+k] \quad (13)$$

- k: Lag index.

V. Results

A. Laboratory Validation

Initially, the system was tested on 6 wheelchairs for a period of three weeks. Feedback from actual users participating in the pilot study was important, since it provided essential information for validation purposes and for rating system usability. The picture presented in Fig. 6 shows a wheelchair with the attached Motion Logger.

Preliminary tests were carried out in a laboratory environment with wheelchairs provided by the VA hospital to the Motion-Logger design team. Numerous experiments were carried out using other measurement instruments which provided ground-truth information, among them, video-taped experiments. Based on these controlled experiments, it was determined that an accuracy of ± 3 degrees in dynamic roll and pitch estimation was achieved.

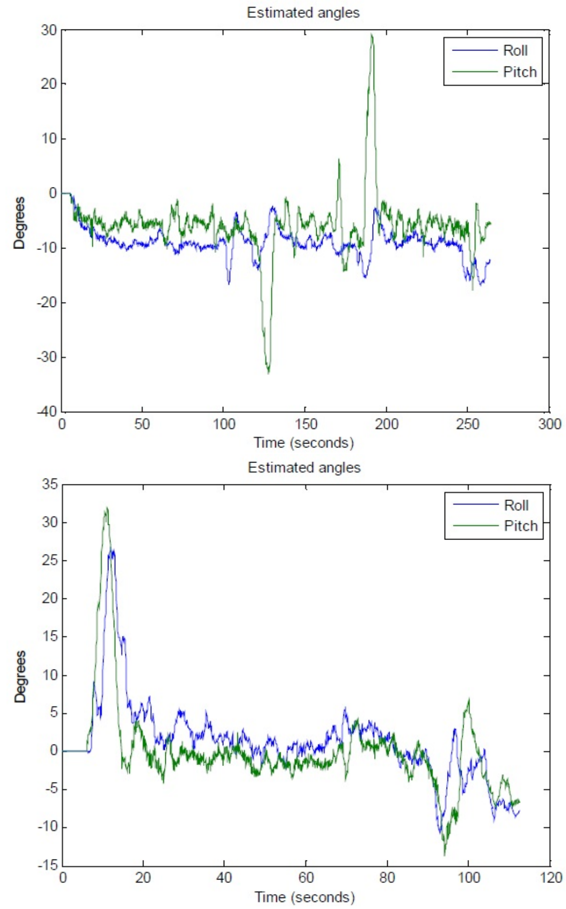

Fig. 7. Pitch and Roll variations during tip detection for Subject #4.

B. Prototype Deployment

For the final deployment, 50 Motion Loggers were assembled, tested and delivered for installation. The functionality of each device was properly verified by executing an experiment in which roll and pitch angles were forced to known positive and negative values. Thus, connections and sensors orientation were checked. This preliminary experiment was also used to estimate sensors' gains and dynamic ranges specific to each device. The purpose of this final stage of the study was to determine tips and falls by wheelchairs users based on the estimated angles. The devices were installed and the SD cards were replaced monthly. Once the memory with the logged data arrived it was processed using the

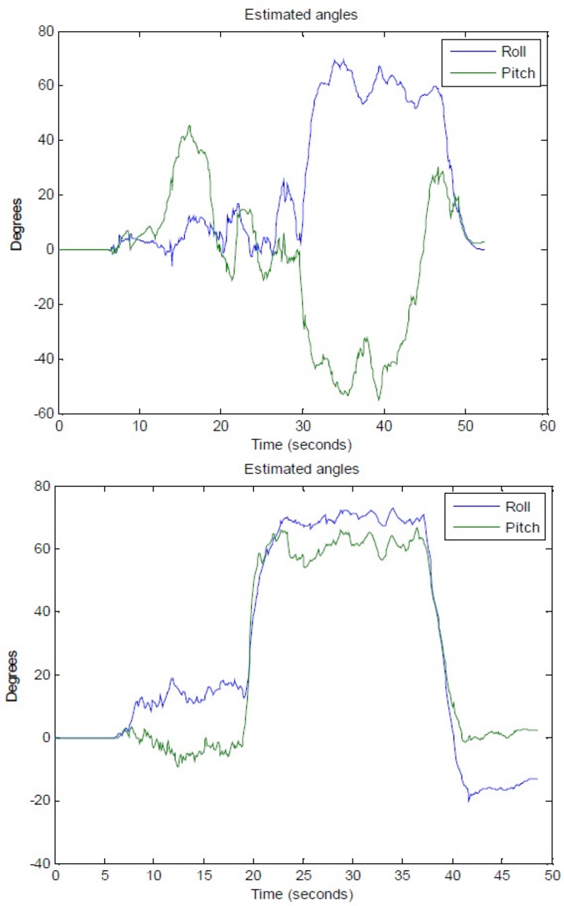

Fig. 8. Angles' variations during fall detection for Subject #4 and #17.

algorithm for estimating pitch and roll. The processed data was used to determine when tips or falls may have occurred. Statistically relevant results based on the utilization of the motion determination solution will be presented in future publications. Fig. 7 shows the results obtained after running the estimation algorithm on data collected from users who logged information for several weeks. It corresponds to the variation of angles during a frame when a tip was detected for subject #4. Fig. 8 shows frames where a fall was detected for subjects #4 and #17.

VI. Conclusions

A Motion-Logger was successfully developed to support the study of tips and falls of wheelchair users. A logging and estimation system provided accurate information about the motion and attitude of the wheelchair for successfully determining risky situations. The system was designed to collect data for long periods of time, which could be several months. The data, from sensors containing relevant information about the motion of the wheelchair, was stored in an SD memory card. Data was also obtained and stored for battery condition and temperature. The date and time at which the data was recorded was included for further analysis.

When the wheelchair data is combined with demographic records the solution provides important information regarding the nature of risks encountered by wheelchair users. In addition, the solution provides for the investigation of the nature, causes, consequences and costs of wheelchair users falls.

Current work is focused on improving the Kalman filter algorithm and on evaluating the possibility of implementing the angles estimation algorithm and the tips and falls detection software in the embedded device instead of in an external computer.

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