MOBILE SPEED AND POSITION SENSOR FOR HOME HEALTH MONITORING BASED ON ACCELEROMETER SIGNALS

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Keywords: Sensor signal processing, Sensor fusion, Home health monitoring.

Abstract: This paper presents a study how accelerometer sensors can be used to estimate speed and position by integrating the sensor signals once and twice, respectively. Unfortunately, integration emphasises bias and noise of the sensor. We developed a heuristic nonlinear filter which efficiently suppresses unwanted effects, assuming human movement. Our aim is to provide a mobile sensor to detect the movement of elderly people suffering from dementia, for home health monitoring purposes. Utilising this sensor together with others allows us to detect unusual behaviour of the patient. The two accelerometer signals together with the suggested heuristic nonlinear filtering allows us to reliable measure the speed, and reconstruct the shape of the movement trajectory of the patient.

1 INTRODUCTION

There are many applications which require speed and position measurement of an object with cheap and mobile sensors, which do not obstruct the movement. Our aim is to find an appropriate device for home health monitoring, i.e. to track the movement of elderly people in their home, suffering from dementia. This, together with other sensors in the home might be used to detect unusual behaviour of the patient, and to warn the relatives or the nurse/doctor. There are several types of information which might be useful for this purpose. This includes the current position of the patient in his/her home (which room, which part of the room), speed of the movement, acceleration (e.g. detecting a fall). Even the shape of the trajectory of the movement is useful information to detect whether the patient is moving intentionally into a specific direction or nervously perambulates, walks back and forth, or circulates in the room.

One possibility to extract many of the above features is to install cameras in every room of the house. If two cameras per room are installed, even precise 3 dimensional position reconstruction is possible (Hartley and Zissermann, 2006), although the image processing is not trivial (face recognition, cloaking, more people in the room etc.). This solution has the drawbacks that installation demand and costs are high, and people are very much dismissive about being watched, even if the image itself is not viewed by others, only certain characteristic parameters are extracted from the images. Moreover, reliable information can be retrieved only under certain lighting conditions. If the room is not lit, e.g. at night, cameras cannot be used.

Another possibility to detect position is to use passive infra movement sensors in every room (Scanaill et al., 2006). If more sensors are installed in one room (e.g. into the four upper corners of walls) not only a binary signal is provided (someone resides in the room or not), but also the section within the room can be detected. However, this is still a very rough detection of the position, no other information can be extracted from the measurement and requires many wiring in the house, which might bother the patient.

RFID is also a good idea (Mateska et al. 2011). However, the range of the detection of RFID tags is limited, thus many RFID readers have to be installed, which increases the installation time and cost, and the room would be full of wires. This approach aims to detect only the position.

In this research we investigated the possibilities of utilising accelerometer sensors to measure the acceleration, and estimate the speed and position by integrating the signals. The idea is to put the tiny accelerometer into regularly worn clothes or even

Dabóczi T. and Kalvach A..
MOBILE SPEED AND POSITION SENSOR FOR HOME HEALTH MONITORING BASED ON ACCELEROMETER SIGNALS.
DOI: 10.5220/0003790603500354
In *Proceedings of the International Conference on Biomedical Electronics and Devices* (BIODEVICES-2012), pages 350-354
ISBN: 978-989-8425-91-1

better into the slipper. The collected signal can be occasionally transmitted by wireless sensor network to a gateway, to spare battery life. With this approach we aim to provide information about the acceleration and speed of the patient, and about the shape of the trajectory of the movement. Precise position estimation seemed to be impossible after double integration; however, the shape of the movement is reliable reconstructed. Integration emphasises the bias and noise of the measurement more and more as the time goes. With double integration the effect is even stronger. Pure double integration provides useless estimate. We developed a nonlinear heuristic filter, which takes into account that human movement has certain behaviours (limited speed, acceleration, many times in still etc.).

2 DISTURBING EFFECTS

The speed and position information can be reconstructed from the acceleration by integrating the signal once and twice.

$$v = \int a(t)dt\,, \quad x = \iint a(t)dtdt\,, \tag{1}$$

where x denotes the position, v denotes speed, a denotes the acceleration and t stands for time. Since the three dimensions in the space are independent, position in the 2 or 3D space can be reconstructed by independently integrating the different (orthogonal) components. If the acceleration signal is available as sampled data, we can estimate the integral by simple accumulation of the samples:

$$v[i] = \Delta t \sum a[i], \qquad x[i] = \Delta t^2 \sum \sum a[i], \tag{2}$$

where [i] stands for the sampled version of the corresponding signal and Δt denotes sampling time. Here we assume equidistant sampling.

However, if the accelerometer sensor is not perfect, we will integrate all biases and disturbances also. We need to face offset error, gain error, offset drift, wideband electric noise and quantization noise.

$$\hat{x}[i] = \Delta t^2 \sum \sum (G \cdot a[i] + e), \tag{3}$$

where G denotes gain error and e stands for all offset like errors, including wide band electric and quantization noise.

Offset-, gain error, offset drift and wideband electric noise are caused by the sensor itself, while quantization noise is produced by the AD converter. We could model other disturbances of the AD converter also, like e.g. integral nonlinearity, however, using a small resolution ADC (8..10 bits) these disturbances can be neglected compared to the others. A short measurement of one of the two independent 3D accelerometers is shown in Fig. 1., having still sensors. It can be observed that there is quite a large noise on the signals. The two sensors – each having 3 axes – have slightly different offset and gain errors. The channel, showing around 9 m/s^2 corresponds approximately to the direction of the gravity. (Sensors were not precisely positioned to align with the horizontal and vertical directions.)

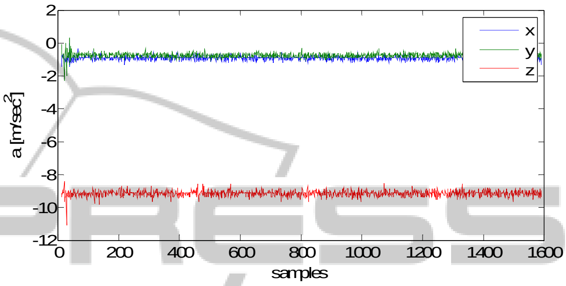

Figure 1: 3D accelerometer signals in still position.

We observed that offset error is always present, and is characteristic to a particular sensor. Thus, we can compensate for them after a short calibration procedure. Unfortunately, offset error changes with the temperature, thus a one time calibration remains valid only until the temperature does not change significantly. In our application we can assume that room temperature does not change abruptly and much, thus we do not compensate the sensor signal for offset drift. Gain error can be compensated utilizing offline calibration measurements.

Wide band electric noise and quantization noise can be treated together. They all have the following properties: they have a symmetric probability density function with zero mean value, and they have a wide and approximately white spectral distribution. After integrating the acceleration signal the variance of the speed estimate increases with the square of time. After double integration the variance of the position estimate is increased already with the fourth power of time. Fig. 2 shows the first and second integral of a Gaussian noise having symmetric probability density function with zero mean value.

In the remaining we will focus on compensating the effect of the offset error and the noise.

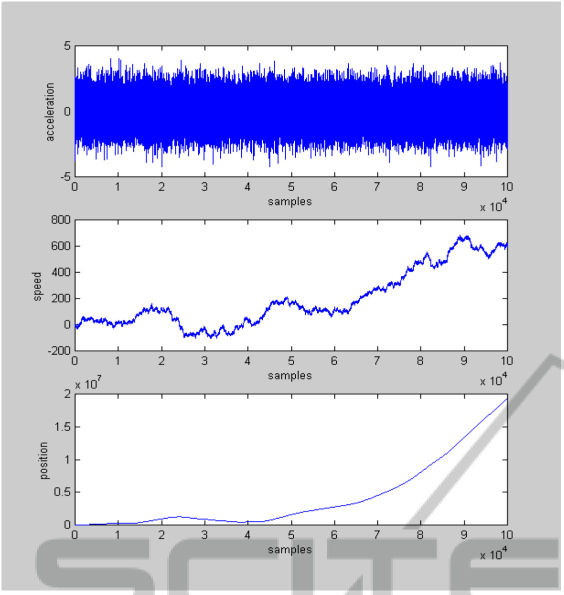

Figure 2: First- (middle figure) and second integral (lower figure) of a Gaussian noise (upper figure).

3 HARDWARE SETUP OF THE EXPERIMENT

In order to verify the behaviour of our position estimator we set up a sensor system. Our department developed a modular platform for embedded systems (Tóth et. al, 2005), which we used as a rapid prototyping device. We integrated two accelerometers to the 8 bit microcontroller system, each having a $\pm$3g range in all 3 axes. This range seemed to cover all acceleration resulted from the movement of an elderly man/woman, taking into account that gravity adds to the signal in one direction. The sensor has a proportional analog output, thus we need a 6 channel AD converter to digitize the signals. The ATMega128 microcontroller of the rapid prototyping system has a built in ADC, with 10 bits resolution. The sampling frequency is set to 162 Hz (corresponding to ~6 msec sampling period for each channel). The sampled acceleration signals can be retrieved from the embedded system either through wired serial port, or wireless link in the ISM frequency band (433 MHz).

4 SPEED AND POSITION ESTIMATION

The speed signal can be calculated from the acceleration signal by means of integration, while position with double integration. As we concluded in the first section we can focus on offset error and noises as the main disturbing effects of the integration. First we will assume that the movement is in a horizontal plane, and the sensor itself does not rotate. Later in Section 5 and 6 we will investigate the effect of the rotation and the gravity.

The offset error can theoretically be removed by suppressing the DC component. Real time suppression of the DC component with a very narrow suppression band highpass filter would require long FIR filter, which means on one hand a large delay, on the other hand very large computation demand. Here we were satisfied with offline computation of a larger data set, carried out in a PC, where data was collected regularly from the embedded sensor system. In that case the constant offset throughout the dataset was considered the mean value of the record, which was removed from the acceleration signals (each channel separately).

The noise can be handled in several ways. We implemented two accelerometers, which provide measurements from the same movement with uncorrelated noise, and independent disturbances (offset error, bias etc.). Our first attempt to reduce the effect of the noise is to average the corresponding channels of the two sensors. Cross correlation of the same channel of the two sensors proves that the noise can be treated as uncorrelated. The noise variance is thus reduced.

The second attempt to reduce the effect of the noise is an appropriate filtering. Human movement has certain bandwidth. Thus, filtering out components that are out of the supposed bands reduces the noise variance. We tried to filter the speed signal. Our concept is that human movement has the characteristics that speed is zero in most of the time. A very low speed motion is not realistic; it will be handled as cause of error of integration. Thus, we need to observe the baseline shift of the speed signal, and compensate the speed measurement for that.

4.1 Linear and Order Statistic Filtering

As the baseline we want to estimate has very low frequency components first we applied a narrow-band linear lowpass filter. However, this filtering brought no satisfactory results. It is hard to sharply separate the baseline and human movement. We skipped this possibility.

Our second attempt to filter the speed signal was an order statistic, nonlinear filter, namely the median filter. It has the advantage that impulse like noises can be efficiently removed. In that context short movements will be treated as "impulses", and we assume that the patient remains still most of the time. The window size of the median filter needs to be fitted to the possible length of the duration of the movements (couple of seconds). This solution has much better performance than linear filtering, however, still not good enough.

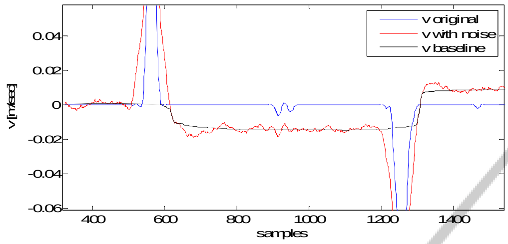

Figure 3: Baseline removal of the speed signal by means of median filter.

4.2 Heuristic Nonlinear Filtering

We propose to use a heuristic nonlinear filter. The main principle of the filter is that we are looking for long parts of the signal which have nearly constant speed. These parts will be considered as zero-speed parts, and the deviation will be treated as disturbance. Between the constant speed parts the baseline will be linearly interpolated. This method has the advantage over median filtering that we get an acceptable estimate for the baseline even during the movement, and the baseline estimate will be a continual function.

Fig. 4 shows a simulation result with the proposed filter. Recording the movement of the PC mouse carried out the reference measurement. We distorted this signal synthetically and added noise to simulate the real environment. Position is reconstructed with double integration after filtering the speed signal. It can be observed that fractional movements are much better reconstructed than continuous one (Fig. 5). The shape of the trajectory of the movement is reliable reconstructed, while the 2D position information is distorted after double integration.

5 CORRECTION OF SENSOR ROTATION

In the previous section we assumed a horizontal movement, where the coordinate system of the world and the sensor are aligned. If the sensor itself rotates, this assumption is not valid any more. We need to detect this situation and correct the signals appropriately.

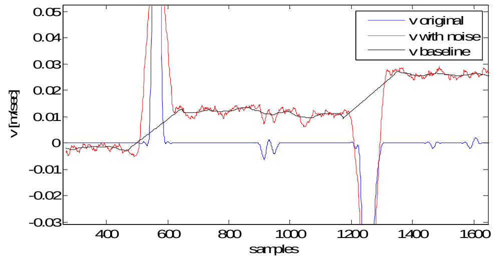

Figure 4: Baseline removal of the speed signal by means of the proposed heuristic filter.

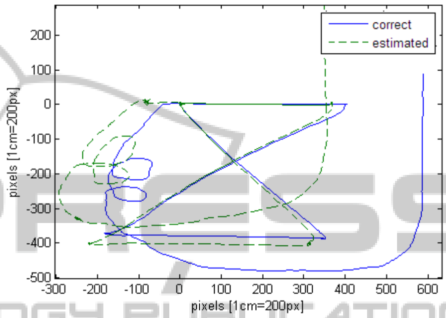

Figure 5: Position estimation in 2 dimensions.

We can make use of the fact that we have two sensors of the same type. If there is no rotation, the two sensors measure the same acceleration, apart from bias and noise. If the sensors are rotated, there will be a difference in the accelerations. Averaging the two signals reduces the noise and provides an acceleration estimate for the point in-between the two sensors, and cancelling the effect of rotation. Thus, we can separate acceleration and angular acceleration.

Averaged signals depend only on acceleration, while the difference of the two sensors depends only on the angular acceleration, assuming that the axes of the two sensors are aligned well enough. In this case if the sensors are rotated with β angular acceleration around the point halfway between the two sensors, both sensors will measure an additional acceleration component, perpendicular to the axes connecting the sensors (Fig. 6.).

The angular acceleration can be calculated from the two measurements as follows:

$$\hat{\beta} = \frac{a_{1y} - a_{2y}}{2r}, \tag{4}$$

where $\hat{\beta}$ denotes the estimate of the angular acceleration, a_{1y} and a_{2y} are the acceleration components perpendicular to the axes connecting the sensors, and r denotes the radius of rotation (half of the distance between the sensors). After compensating with this component we can use the former methods to integrate the signals.

The accuracy can be increased by a stronger lowpass filtering of the angular acceleration signal, since it can be assumed that angular acceleration has a very low frequency.

In a non-ideal case the two sensors cannot be perfectly aligned in the space on the printed circuit board, thus, there will be a mismatch in the direction of the axes. This results a difference in the acceleration signals of the two sensors even without rotation. The observed “false” angular acceleration depends on the acceleration and the angle between the axes of the two sensors. The angle mismatch is distorted by a trigonometric function (sin(x)). For small angles the sine function might be approximated by its argument. The angle mismatch should be determined based on offline calibration measurements. This should be done only once, after the soldering of the sensor. However, knowing this component means that the measured acceleration needs to be compensated regularly with $\sin(\varphi)a_x$. Please note that in this case the axis x is the “average” of the two axes of sensors.

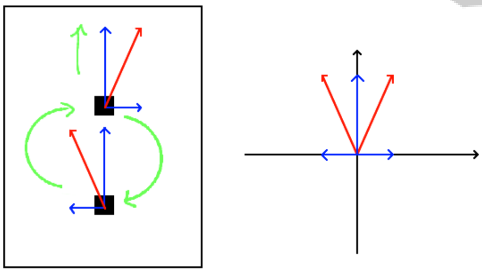

Figure 6: Effect of the rotation of the sensors, together with acceleration.

6 EFFECT OF GRAVITY

In the former sections we neglected the effect of gravity as we assumed a horizontal motion. In the case the sensors are not constantly moving in horizontal plane, the gravity adds an extra acceleration to the sensor signals. Fortunately these additional accelerations are constant while the sensors are not moving. The heuristic filter – which we have applied on the speed signal – is designed for this case. Thus, applying the same heuristic filter on the acceleration signal can cancel the effect of gravity.

We can improve the gravity cancellation by using the rotation estimation. If we apply 3D accelerometers, we can calculate a 3 dimensional rotation and so the direction of gravity. After this the gravity components can be subtracted from the signals. In order to make a good gravity cancellation, the two methods should be applied together.

7 CONCLUSIONS

In this paper we investigated the use of two accelerometers to measure the acceleration and estimate the speed and position of elderly people suffering from dementia, for home health monitoring purposes.

We developed a heuristic filter to suppress the measurement disturbances, which would make the estimate impossible because of the integration of the raw signal data. We also developed an algorithm to detect and correct for the rotation of the sensors. Fabrication or installation mismatch of the axes of acceleration sensors can also cause problem, for which we developed also a compensation method.

Simulation and measurement experiments show that speed estimate is quite reliable based on one time integration, after utilising the proposed heuristic nonlinear filter. Precise position estimate not possible, however, in the case of fractal movement the shape of the trajectory can be well reconstructed, which is a useful information about the patient.

ACKNOWLEDGEMENTS

This work has been supported by BelAmi and Hungarian Scientific Research Fund (OTKA), grant number TS-73496. Support of Bolyai János Scholarship is also acknowledged.

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