Human Walking Analysis Assisted by DGPS

Quentin Ladetto[1], Vincent Gabaglio[1], Bertrand Merminod[1], Philippe Terrier[2], Yves Schutz[2]

[1]*Geodetic Laboratory, Institute of Geomatics, Swiss Federal Institute of Technology, Lausanne, Switzerland*

[2]*Institute of Physiology, University of Lausanne, Switzerland*

BIOGRAPHY

Quentin Ladetto is a Ph.D. candidate in the Geodetic Engineering Laboratory at the Swiss Federal Institute of Technology in Lausanne (EPFL). He holds a M.Sc. in Surveying Engineering from the same University. His present research focuses on INS-GPS integration for human positioning.

Vincent Gabaglio is a Ph.D. candidate in the Geodetic Engineering Laboratory at the EPFL. He holds a M.Sc. in Surveying Engineering from the same University. He currently investigates on algorithms for a dead-reckoning navigation system for people and its integration with GPS positioning.

Bertrand Merminod is ordinary Professor at the Geodetic Engineering Laboratory (EPFL). He earned his M.Surv. at the University of New South Wales (Australia) before working as geodesist in Lesotho for the Swiss Development Co-operation as well as product manager with Leica.

Philippe Terrier is a PhD student graduated in Biology at the University of Lausanne. He obtained a diploma in biomedical engineering at the EPFL. His research projects deal with new methods to study energy expenditure induced by locomotion.

Yves Schutz got his PhD at the University of California in Berkeley (USA) and is currently lecturer in Physiology at the Faculty of Medicine (University of Lausanne). His interest relates to the energy requirement of human and the relationship between physical activity, sports and health.

ABSTRACT

The recent advent of high sampling frequency GPS receivers opens new perspectives for the analysis of human walking pattern. Coupling satellite signal with tri-axial accelerometry gives important information on the step length of individuals. The stride length variability directly influences dead reckoning for on-foot navigation when the position cannot be computed by double integration of the antero-posterior acceleration. The main reasons are the alignment problem and the important sensor systematic errors in comparison with human walking speed. However, raw acceleration signals can provide helpful information on both the velocity and the walk dynamics. Different tests were conducted to assess the stride length as a function of several cumulative parameters such as slope and step frequency. As such parameters naturally vary, a continuous adjustment is necessary. This paper presents a physiological approach for an individual stride calibration as basis for global pedestrian dead reckoning applications. This study lies within the framework of a project that aims at analysing the daily activity of people. Precise continuous positioning appears of evident interest.

1. INTRODUCTION

"227 steps East from the Holy Cross, then 175 steps South and you'll find the treasure location." This novelistic description of a determined trajectory serves as basis for modern on foot navigation applications. If satellite signals are available, accurate positions can be computed by differential GPS and the receiver will guide one directly to the coveted treasure. Under a dense vegetal canopy or in urban canyons where GPS data cannot be picked up, the positioning strategy changes and the length of the steps will greatly influence the location of the digging.

If counting strides appears an intuitive means to calculate a travelled distance, the considered step length directly influence the computed approximation. This more common way of displacement is function of numerous complex physiological processes, which are difficult to model. Like the wheel circumference for cars, the stride length is the fundamental parameter for pedestrian dead reckoning strategies. If dead reckoning for vehicle can be satisfactorily solved by means of inertial and map matching technologies, a similar approach is difficult to adopt for on foot navigation. The main reason is that the systematic errors present in a small Inertial Measurement Unit (IMU) are too important in comparison with human walking speed. Therefore, positions cannot be computed by double integration of the acceleration. An alternative is to use the accelerometer signal pattern to deduce the step occurrences and continuous heading information supplied by magnetic field sensors. Considering an appropriate stride, taking the pace count and multiplying it by the step length will provide the covered distance (Judd 1997, Gabaglio 1999, Ladetto et al. 1999).

As the human stride is everything but constant, a continuous step calibration is necessary. Within the range of variation of the step length, the required precision is at the centimetre level. Such required accuracy is commonly reached after determining the cycle ambiguities of the carrier phase observations for each satellite (Leick 1994). However, for short baselines (less than 5 km), both phase and differential code solutions (differentiation of 2 successive positions) match within 5 cm (Perrin 1999). This permits to work with code solutions that are more convenient for this kind of application.

The length of a stride can be modelled as a function of several parameters such as the step frequency and the accelerometer signal covariance. The biological step length variability has to be taken into account for a realistic approach. All physiological characteristics will be considered during the dead reckoning procedure involving wavelet pre-processing of the signal and both complementary recursive prediction and adaptive Kalman filtering. In order to better understand the influence of these parameters, several tests were made in real-life situation of outdoor walking. This paper focuses on the step length determination as well as the inter- and intra-individual variability of locomotion in function of external (for instance slope) and internal factors (for instance metabolic energy requirement).

The structure of the paper is as follows. First, a description of the accelerometer signal as well as the analyzed step pattern is given. Then the analysis of several tests bringing to the fore the main parameters used for step length modelisation during both GPS signal availability and dead reckoning periods is done. Finally, the assessment with GPS of the external mechanical work of walking is discussed.

2. DETECTING STEP OCCURENCES

All the necessary information to detect a step occurrence is found in accelerometer signal. Using the same example, detection algorithms can be applied on both the vertical and antero-posterior signals. Several identification strategies are possible, but we show the one that appears to give the most robust results with the least computation time. The global idea is to localize maxima within a fixed interval. The size of this interval depends on the analyzed signal. When working with vertical acceleration, a pattern of two peaks, close in time, can appear at each step depending where the sensors are placed on the body These correspond to the impacts of the heel and of the sole with the ground. The heel impact normally shows the biggest value for flat and light incline walks, but the pattern also varies from one person to the other. Mechanics of walking completely changes once the slope is becoming greater than 10%.

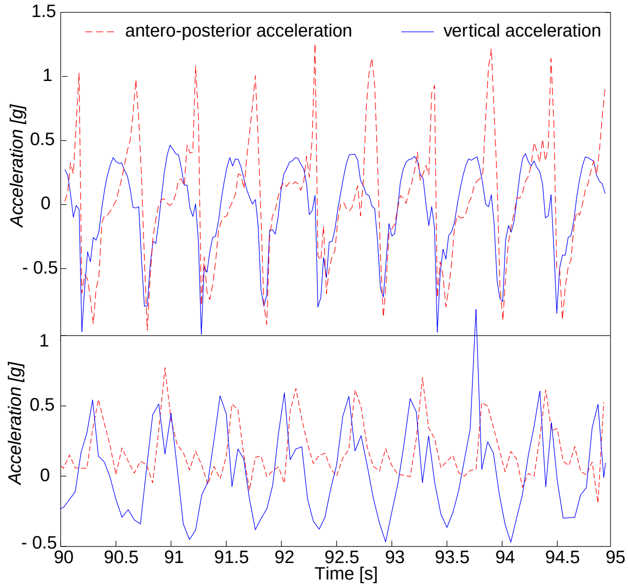

Figure 1: Typically shifted antero-posterior and vertical acceleration pattern while walking. Sensors are placed on the low back (up) or on the thorax (low).

The antero-posterior acceleration presents one main maximum, corresponding to the heel impact, as can be seen in Figure 1. Physically, this represents the forward displacement of the body. Ideally integrating this signal twice, after the attitude determination of the IMU, should permit to deduce the step length. The step identification using the presence of both shifted peaks should be considered as the most physiologically correct strategy. The rapid and brief variation of both individual accelerations allows to work with only one signal to give a robust step detection. A combined analysis has been tested using both signals together, and it validated the chosen approach.

As one step will be defined as the traveled distance between two heel impacts, this introduces a necessary notion of time interval between them. If a maximum peak is not followed, after a certain time, by another one, the person is still considered at the previous location. Such singularities generally occur during short and non regular walking periods.

Taking wrong time intervals will give an over(-under) evaluated number of steps. In dead reckoning mode, this rapidly leads to errors of tens of meter in long traveled distances. Such an error source can be partially removed by pre-processing the signal, computing wavelet transformation (Matlab 1998, Thonet et al 1998). This provides a more smoothed signal where the acceleration pattern is lost to the benefit of a better shape.

The original signal passes through two complementary filters. It is divided into its low frequencies (approximation) and high frequencies (detail) components. By iterating this process n times on the resulting approximation, the signal is broken into lower resolution components. This is called the wavelet decomposition tree, and n is the number of computed levels. The choice of the wavelet family is function of the signal characteristics to analyze. In the present application, the pattern of the acceleration is lost to the benefit of a better shape. Figure 2 presents both raw and pre-processed data using the Meyer wavelet function. The signal decomposition was performed at level 4. The detail at this level reproduces the step frequency very well, with one maxima only at each occurrence.

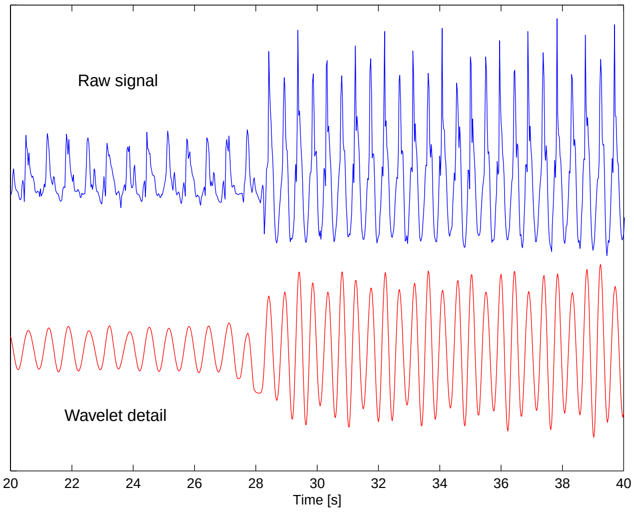

Figure 2: Raw and pre-processed signal using Meyer wavelet function at level 4 decomposition.

3. INDIVIDUAL VARAIBILITY

Because a good knowledge of the gait pattern is of major importance for dead reckoning, we also performed different experiments to highlight the inter- and intra-individual variability of locomotion in function of external (for instance slope) and internal factors (for instance metabolic energy requirement).
Fourteen subjects, nine men and five women, aged between 21 and 28 participated in the study. Subjects characteristics were (mean ± SD): age: 24.6±2.4 yr. Weight: 73.9±11.9 kg (with the weight of the devices). Height: 174±9 cm. Body Mass Index (BMI): 21.7±2.5 kg/m2 (without the weight of the devices).

The study took place along a circuit on which the subjects had to walk twice at their own pace and without external constraints except wearing the GPS receiver. The total length for one run was 1310 meters and the cumulated uphill height difference was 67 meters. There were flat sections but the slope exceeded 17 percents for some other sections.

The precise positioning of the subjects was realised with two Leica System 500 double frequency GPS receivers, measuring at a 5 Hz rate in differential phase mode.

Four parameters were averaged from GPS data over 7 seconds periods: walking speed, stride frequency (assessed by Fourier transform analysis), stride length (calculated from speed and stride frequency), and slope. The different parameters were sorted according to the slope into 5 categories: very down (<-9%), down (-3%-9%), level (-3%-+3%), up (+3-+9%), very up (>+9%).

The aim of the study was to analyse how people adapt their gait in function of incline.

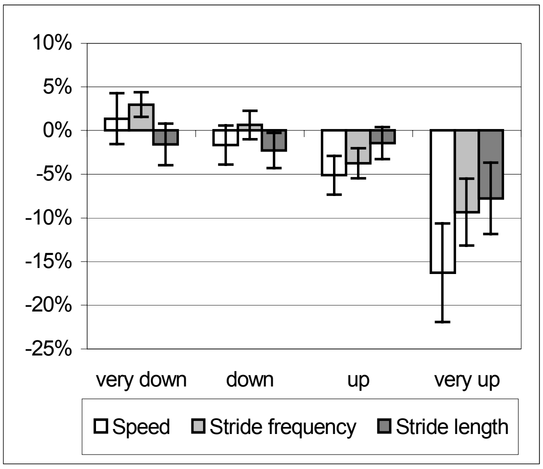

Figure 3. Adaptation of the gait to the slope. Bars are the relative difference between level walking (-3% to +3% slope) and the uphill or downhill walking. Data are mean (N=14) +/- SD.

The results show that the subjects did not modify significantly their walking speed in downhill walking as compared to level walking. They slowed down (-15.3%) only in very steep uphill sections of the circuit (>+10% incline). This speed change was induced primarily by a reduction of SF. It has to be stressed that a large inter-individual variation was observed. These results may be taken into account for dead-reckoning purposes because important slope modify the step length.

4. MODELING THE STEP LENGTH

Taking into account all precedent observations, the predicted step length will be computed using the following equation:

$$\text{Step length} = A + B \cdot \text{Freq} + C \cdot \text{Var} + w \quad (1)$$

A, B, C : Computed parameters by linear regression

Freq : Actual step frequency

Var : Variance of the signal

w : Gaussian noise N~(0, σ)

The step frequency can be determined with a changing number of occurrences using a Fast Fourier Transformation (FFT) or by time differencing the maxima. Since the dynamic of walk can change very rapidly, the smaller the calibration period, the quicker the adaptation of the estimated value. The estimation quality will then directly depend of the "individually" computed parameters of the regression. Once determined, they are fixed per person for the interval inside which the step sizes are varying without any possible update (no GPS dada available). The continuous interval variation and recalibration is realized through the use of an adaptive Kalman filter (Kalman 1960, Brown & Hwang 1997).

The adaptive context comes from the processing noise uncertainty and variability. In this application, no standard values are available. The most probable value comes from examining the physics of the problem. The processing noise represents here the uncertainty by which the predicted step length can match the true value. As filtered steps values are supposed constant for a definite interval, the bigger the residuals with the predicted steps length are, the bigger the processing noise value is. Computing the Gaussian distribution of this residuals will give an information about the processing noise.

5. CONTINUOUS STEP CALIBRATION

Let us now apply the recursive least squares steps length prediction when no GPS data are available. The number of steps taken into account to predict the next value will influence the time response of the filter to an abrupt change in the step length (e.g. walk → run). The different tests were conducted with a 20 steps update period. All studies made on an average of 20 people brought to the fore that the step length is more irregular when walking slowly. Values might vary from 4% at 130 steps/min rate walk to 15% for a 60 steps/min walk. If we consider a mean step value of 75 cm, the standard deviation of the step length varies from 3 cm to 11 cm depending on the frequency.

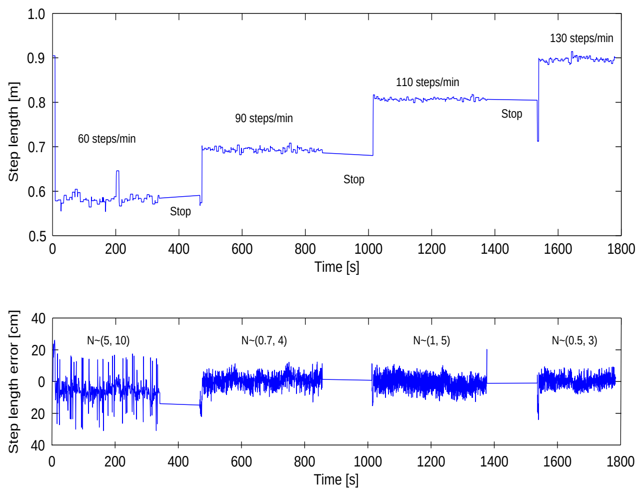

Figure 4: Predicted step values at different frequencies with normal distribution of the error.

Taking into account this biological characteristic, a following prediction procedure is adopted:

1. Consider a constant step value S on the interval of t steps
2. Compute the residuals between S and the predicted value using equation (1)
3. Estimate the mean and the variance of the normal distribution of these residuals $N\sim(\mu, \sigma)$.
4. Compute the next constant $S = S+\mu$

This approach takes into account the "natural" behavior of human walk. Although steps are not constant, they are normally varying around a more stable value. The presented procedure tries to take advantage of this property considering the Gaussian noise distribution. At the same time, it smoothes the effect of possible outlier values that can happen with singular individual accelerometer measurement. Figure 4 displays the predicted step values at different frequencies, showing the internal variance of the steps. As mentioned earlier, the biggest variance occurs at the lowest frequency.

When GPS data are available, they will permit both a recalibration of the step length and the computation of the regression parameters of equation (1). The state space of the adaptive Kalman filter is then:

$$\text{Step}(k) = \text{step}(k-1) + u(k-1)$$

$$\text{Distance (GPS)/\# of steps} = \text{step}(k) + n(k)$$

Both noises are assumed to be Gaussian. The measurement noise is fixed to N~(0, 5 [cm]), and the process noise is initialized with N~(0, 10 [cm]). The state matrix is fixed to the identity and the observation matrix simply equal to 1.

If GPS measurements occur at one walking frequency only, the update is done only on the A parameter of (1). It corresponds to the average step value. Other parameters are kept to the previous values until new frequencies can be observed.

The adaptive Kalman filter supply an adaptation of the model to a changing walking dynamic of the person. Figure 5 presents both the recursive prediction and the adaptive Kalman filtered value of steps length after a change in walking dynamic. It is apparent that the recursive prediction model alone is unable to correctly predict accurate changes in step length.

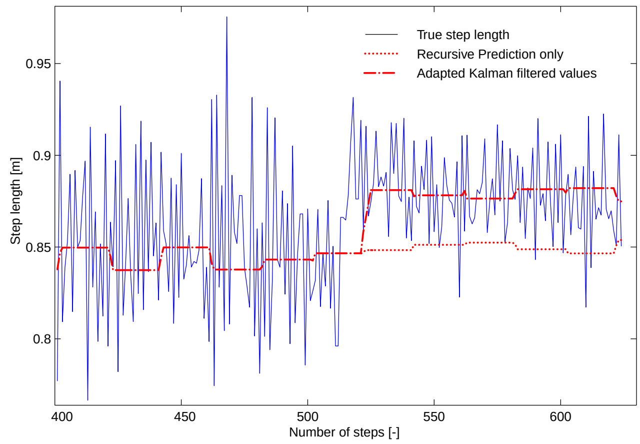

Figure 5: Necessity to re-parameterize the predictive equation by mean of adaptive Kalman filtering.

6. ASSESSING THE EXTERNAL MECHANICAL WORK

Human locomotion involves a metabolic energy cost. The muscles provide forces to move the limbs relatively to the centre of gravity and finally to displace the entire body. The bipedal locomotion mechanisms imply a vertical lift of the trunk and a acceleration/deceleration of the body at each step. The work against inertial forces (kinetic energy variation) and against gravity (potential energy variation) are the origin of the effective metabolic energy cost of walking. The external mechanical work of locomotion has been extensively studied under laboratory conditions by using 3D-video analysis. We tested whether new high precision GPS receivers could provide a sufficient accuracy to record mechanical work outdoors.

Gross metabolic Energy Expenditure (W)	324 ±76
Vertical lift of the trunk (mm)	55 ±14
Power against gravity (W)	70 ±27
Speed variation around average walking speed (m/s)	0.17 ±0.03
Power against inertia (W)	19 ±7
Total mechanical power (W)	72 ±35
Gross mechanical efficiency (%)	21% ±6

Table 1. Assessing external mechanical work of walking by using DGPS. The mechanical work necessary to lift and to decelerate/accelerate the body mass (respectively work against gravity and work against inertia) was divided by the time in order to obtain power. The mechanical efficiency is the mechanical power divided by the metabolic energy expenditure.. Data are mean +/- SD (N=5).

Five subjects walked during 5 minutes on an athletics track. A differential GPS system measured the variation of the position of the trunk at 5Hz. A portable indirect calorimeter recorded breath-by-breath metabolic energy expenditure. It was possible to compute work against gravity, work against inertia and total external work. The well-known temporal shift between work against gravity and work against inertial forces (rolling egg model) was observed. We found a good correlation between mechanical external power calculated from GPS data and energy expenditure assessed by indirect calorimetry.

SUMMARY AND CONCLUSION

Facing the wonderful complexity of human beings, it appears evident that, as mentioned by the English poet Abraham Cowley : "The world is a scene of changes and to be constant in Nature were inconstancy!". Because stride length is the fundamental parameter for pedestrian dead reckoning strategies, a continuous calibration is necessary to avoid cumulated distance errors. Contrary to classical INS-GPS applications, the accelerometer signal is not integrated here to deduce the position, but used to localize step occurrences. Several modelisation limits appears, not occasioned by sensor bias, but by individual natural walking characteristics from which we can cautiously derive the following observations.

- As steps length is not constant but exhibits a continuous variation around a more stable value, the Gaussian approximation seems the most appropriate model. This concretely means that under-estimated steps length are compensated by over-estimated ones when computing the distance traveled.
- The analyzed tests of several walking frequencies show differences between the effective and predicted distance of less than 2%. For example, this results into a difference of 40.8 m for 2'300 m distance realized in 2'905 steps (i.e. 1.8% error). In other words, this corresponds to a distributed error of 1.4 cm per step. Such value is fully acceptable in view of the previous comments.

We conclude that, thanks to the interaction between surveying engineers (providing expertise in positioning) and human physiologists together with biomechanics specialists (providing expertise in gait analysis), a better knowledge of both dead reckoning and human locomotion can be obtained.

ACKNOWLEDGMENTS

The results presented here are based on studies performed under a project supported by the Swiss National Science Foundation.

REFERENCES

Brown, R. and Hwang, P.Y.C (1997) Introduction to Random Signals And Applied Kalman Filtering, John Wiley & Sons Inc., New-York.

Gabaglio, V. and Merminod B. (1999) "Real Time Calibration of Length of Steps with GPS and Accelerometers" GNSS '99, Genova, Italia, October 5-8, 1999.

Judd, T. (1997) "A personal Dead Reckoning Module" ION GPS-97, Kansas City, Missouri, September 16-19, 1997.

Kalman, R.E. (1960) A new approach to linear filtering and prediction problems, Journal of Basic Engineering, Series D 82, pp 34-45.

Ladetto, Q., Merminod, B., Terrier, Ph., Schutz, Y. (1999) "On foot navigation: When GPS alone is not enough" GNSS '99, Genova, Italia, October 5-8, 1999.

Leick, A. (1994) GPS satellite Surveying, Wiley-Interscience, New-York.

MATLAB, (1998) Wavelet Toolbox User's Guide, The MathWorks, Inc., Natick, Mass.

Perrin, O. (1999) Intégration de mesures satellitaires et barométriques pour la localisation 3D, Mensuration, Photogrammétrie, Génie rural 6/99, pp. 320-323.

Perrin, O., Terrier, Ph., Ladetto, Q., Merminod, B., Schutz, Y,. (2000) "Improvement of walking speed prediction by accelerometry using altimetry, validated by DGPS", Medical & Biomedical Engineering & Computing, in press.

Thonet, G., Blanc, O.,Vandergheynst, P., Pruvot, E., Vesin, J.-M., Antoine, J.-P. (1998) Wavelet-Based Detection of Ventricular Ectopic Beats in Heart Rate Signals, Applied Signal Processing, 5:170-181, Springer-Verlag, London.