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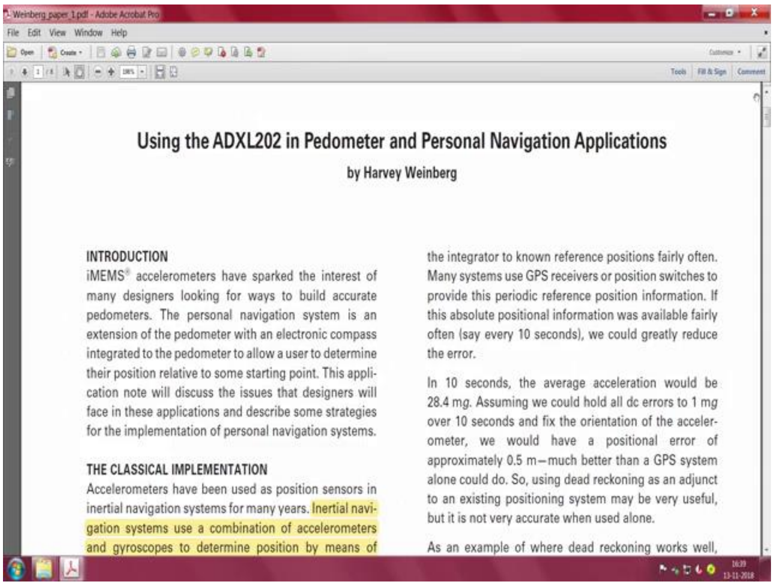
Lecture – 06
Localization using IMU Sensors – II

Now let's discuss some of the advancements that have taken place in this area and how hot a topic this area of pedometer application is actually all about.

Particularly this estimation of stride length , we should spend some time at least here understand basic equations that are associated with this stride length and then look at the advancements in that area and then move on from there.

Let me point you to some material and essentially these are all text book kind of material for your courses and hopefully you will be able to download them including the IEEE and other related publication papers that are associated literature that is there, you should if you read them you will know where the state of art is so, that is the point.

Let us look at the first paper analog devices.


Using the ADXL202 in Pedometer and Personal Navigation Applications

by Harvey Weinberg

INTRODUCTION

iMEMS® accelerometers have sparked the interest of many designers looking for ways to build accurate pedometers. The personal navigation system is an extension of the pedometer with an electronic compass integrated to the pedometer to allow a user to determine their position relative to some starting point. This application note will discuss the issues that designers will face in these applications and describe some strategies for the implementation of personal navigation systems.

THE CLASSICAL IMPLEMENTATION

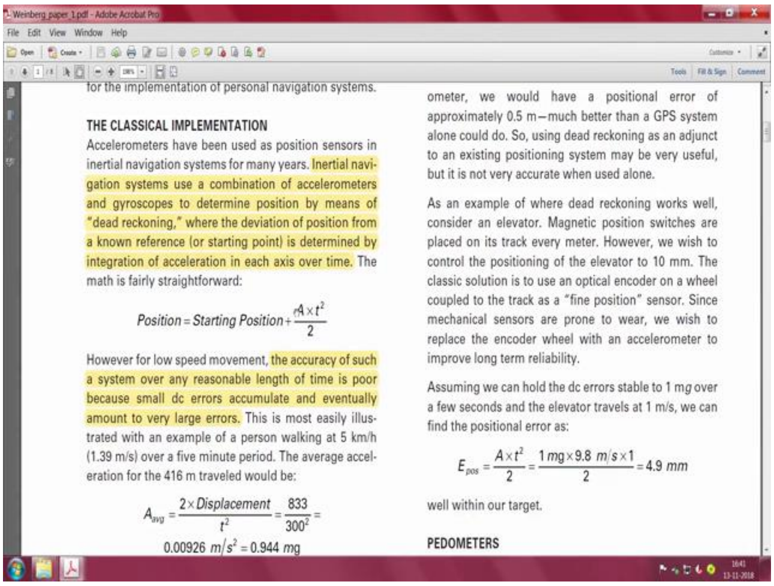
Accelerometers have been used as position sensors in inertial navigation systems for many years. Inertial navigation systems use a combination of accelerometers and gyroscopes to determine position by means of

the integrator to known reference positions fairly often. Many systems use GPS receivers or position switches to provide this periodic reference position information. If this absolute positional information was available fairly often (say every 10 seconds), we could greatly reduce the error.

In 10 seconds, the average acceleration would be 28.4 mg. Assuming we could hold all dc errors to 1 mg over 10 seconds and fix the orientation of the accelerometer, we would have a positional error of approximately 0.5 m—much better than a GPS system alone could do. So, using dead reckoning as an adjunct to an existing positioning system may be very useful, but it is not very accurate when used alone.

As an example of where dead reckoning works well,

This is from a application note from analog devices. It says using the ADXL 202 in a pedometer application. So, essentially it is an accelerometer which they are trying to promote, but apart from that it is useful to see what they actually have in mind. This paper actually gives you that idea of how much the accumulated error can actually be when you do double integration to get to distance. If you do double integration, how integration accumulation errors actually happen is all nicely described in this paper. So, you can download and read it.



for the implementation of personal navigation systems.

THE CLASSICAL IMPLEMENTATION

Accelerometers have been used as position sensors in inertial navigation systems for many years. Inertial navigation systems use a combination of accelerometers and gyroscopes to determine position by means of "dead reckoning," where the deviation of position from a known reference (or starting point) is determined by integration of acceleration in each axis over time. The math is fairly straightforward:

$$Position = Starting\ Position + \frac{A \times t^2}{2}$$

However for low speed movement, the accuracy of such a system over any reasonable length of time is poor because small dc errors accumulate and eventually amount to very large errors. This is most easily illustrated with an example of a person walking at 5 km/h (1.39 m/s) over a five minute period. The average acceleration for the 416 m traveled would be:

$$A_{avg} = \frac{2 \times Displacement}{t^2} = \frac{833}{300^2} = 0.00926\ m/s^2 = 0.944\ mg$$

ometer, we would have a positional error of approximately 0.5 m—much better than a GPS system alone could do. So, using dead reckoning as an adjunct to an existing positioning system may be very useful, but it is not very accurate when used alone.

As an example of where dead reckoning works well, consider an elevator. Magnetic position switches are placed on its track every meter. However, we wish to control the positioning of the elevator to 10 mm. The classic solution is to use an optical encoder on a wheel coupled to the track as a "fine position" sensor. Since mechanical sensors are prone to wear, we wish to replace the encoder wheel with an accelerometer to improve long term reliability.

Assuming we can hold the dc errors stable to 1 mg over a few seconds and the elevator travels at 1 m/s, we can find the positional error as:

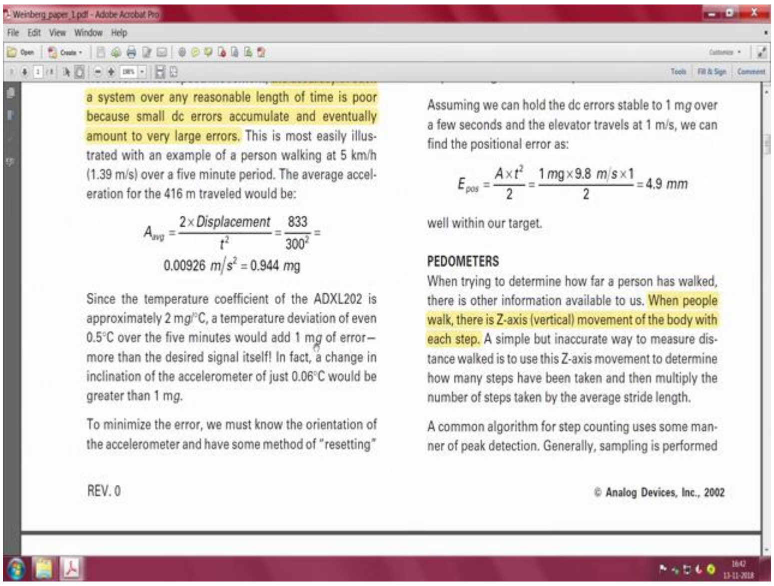
$$E_{pos} = \frac{A \times t^2}{2} = \frac{1\ mg \times 9.8\ m/s \times 1}{2} = 4.9\ mm$$

well within our target.

PEDOMETERS

I have marked some parts in different color and essentially it is saying that inertial navigation systems use a combination of sensors and all that and dead reckoning where the deviation of position from a known reference or a starting point is determined by integration of acceleration in each axis. And this is a very simple expression, this is nothing but, 1/2at^2 which and the initial position or which is essentially ut + (1/2)at^2 a very well known expression.

So, it is essentially doing this 1/2at^2 and how at low speed the accuracy of such system over a reasonable length of time is actually very poor. If you consider the accelerometer.



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$$0.00926\ m/s^2 = 0.944\ mg$$

Since the temperature coefficient of the ADXL202 is approximately 2 mg/°C, a temperature deviation of even 0.5°C over the five minutes would add 1 mg of error—more than the desired signal itself! In fact, a change in inclination of the accelerometer of just 0.06°C would be greater than 1 mg.

To minimize the error, we must know the orientation of the accelerometer and have some method of "resetting"

Assuming we can hold the dc errors stable to 1 mg over a few seconds and the elevator travels at 1 m/s, we can find the positional error as:

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well within our target.

PEDOMETERS

When trying to determine how far a person has walked, there is other information available to us. When people walk, there is Z-axis (vertical) movement of the body with each step. A simple but inaccurate way to measure distance walked is to use this Z-axis movement to determine how many steps have been taken and then multiply the number of steps taken by the average stride length.

A common algorithm for step counting uses some manner of peak detection. Generally, sampling is performed

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It says the temperature coefficient of ADXL is approximately 2 mg per degree Celsius, a temperature deviation of even 0.5 degree Celsius over 5 minutes would add 1 mg of error more than the desired signal itself right so, that is indeed the problem.

And why it is more than this one, because you can see that the desired signal indeed is 0.944 and here you get 1 mg. So, that is indeed much more than the desired signal. In fact, a change in inclination of the accelerometer of just 0.06 degrees Celsius would be greater than 1 mg so, that indeed is indeed causing the problem. So, this paper is written by this person by name Harvey Weinberg and essentially he comes up with a nice expression which we call the Weinberg expression for estimation of stride length.

So, you recall that I showed you a demonstration of the phone and we said that if you take a phone which has 3 axis accelerometer. The Z acceleration is what we will try to use in all the related expressions. So, when people walk there is a Z axis movement and of the body with each step.

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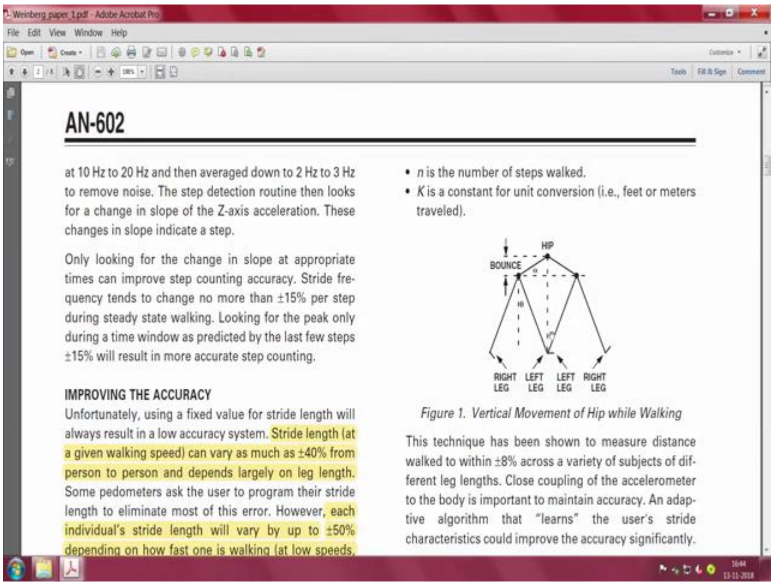
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at 10 Hz to 20 Hz and then averaged down to 2 Hz to 3 Hz to remove noise. The step detection routine then looks for a change in slope of the Z-axis acceleration. These changes in slope indicate a step.

Only looking for the change in slope at appropriate times can improve step counting accuracy. Stride frequency tends to change no more than ±15% per step during steady state walking. Looking for the peak only during a time window as predicted by the last few steps ±15% will result in more accurate step counting.

IMPROVING THE ACCURACY

Unfortunately, using a fixed value for stride length will always result in a low accuracy system. Stride length (at a given walking speed) can vary as much as ±40% from person to person and depends largely on leg length. Some pedometers ask the user to program their stride length to eliminate most of this error. However, each individual's stride length will vary by up to ±50% depending on how fast one is walking (at low speeds,

- n is the number of steps walked.
- K is a constant for unit conversion (i.e., feet or meters traveled).

HIP
BOUNCE
RIGHT LEG
LEFT LEG
LEFT LEG
RIGHT LEG

Figure 1. Vertical Movement of Hip while Walking

This technique has been shown to measure distance walked to within ±8% across a variety of subjects of different leg lengths. Close coupling of the accelerometer to the body is important to maintain accuracy. An adaptive algorithm that "learns" the user's stride characteristics could improve the accuracy significantly.

What actually is happening in the above image is, this is the hip which is of the human and you can see every time there is a right leg you move up and you have the left leg which is placed back. There is a you can assume that the leg is like a lever and such a lever essentially bends exactly at the knee at the knee point and whenever you move this lever flexible lever actually bends at the knee point and that indeed gives a sort of a kick to the accelerator the accelerometer.

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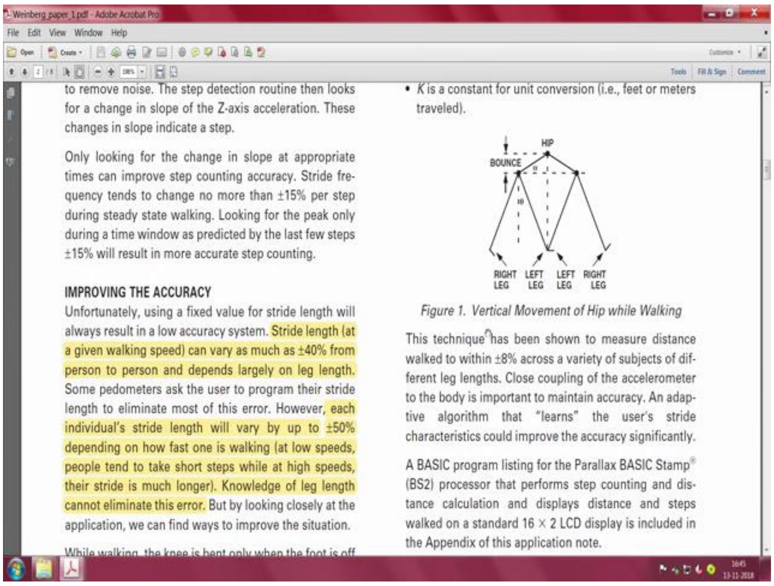
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While walking, the knee is bent only when the foot is off

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BOUNCE
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LEFT LEG
RIGHT LEG

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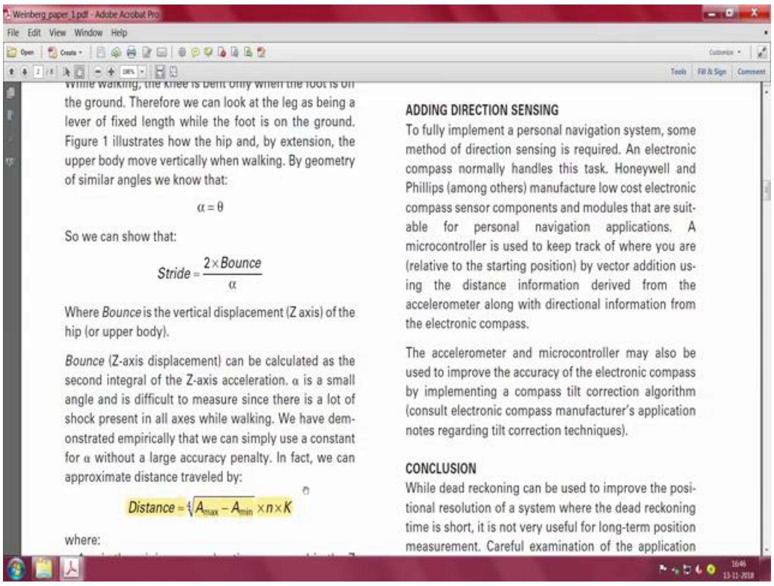
A BASIC program listing for the Parallax BASIC Stamp® (BS2) processor that performs step counting and distance calculation and displays distance and steps walked on a standard 16 × 2 LCD display is included in the Appendix of this application note.

So, essentially this is what the whole idea behind you know the Z axis system you know showing you a sort of a waveform which we discussed previously you get a maximum acceleration and a minimum acceleration essentially happening because of movement of the leg and bending of the knee and therefore, the hip moves up and down and up and down and you can see that all of this is well captured in this nice picture.

So, essentially the stride is nothing, but the movement of this bounce which is shown here. So, if you do you can easily calculate the stride length by this very basic system where bounce is the vertical displacement of the hip. The hip is moving up and down up and down which is the upper body and this hip movement essentially is captured.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the ground. Therefore we can look at the leg as being a lever of fixed length while the foot is on the ground. Figure 1 illustrates how the hip and, by extension, the upper body move vertically when walking. By geometry of similar angles we know that:

$$\alpha = \theta$$

So we can show that:

$$Stride = \frac{2 \times Bounce}{\alpha}$$

Where *Bounce* is the vertical displacement (Z axis) of the hip (or upper body).

Bounce (Z-axis displacement) can be calculated as the second integral of the Z-axis acceleration. α is a small angle and is difficult to measure since there is a lot of shock present in all axes while walking. We have demonstrated empirically that we can simply use a constant for α without a large accuracy penalty. In fact, we can approximate distance traveled by:

$$Distance = \sqrt[4]{A_{max} - A_{min}} \times n \times K$$

where:

ADDING DIRECTION SENSING

To fully implement a personal navigation system, some method of direction sensing is required. An electronic compass normally handles this task. Honeywell and Phillips (among others) manufacture low cost electronic compass sensor components and modules that are suitable for personal navigation applications. A microcontroller is used to keep track of where you are (relative to the starting position) by vector addition using the distance information derived from the accelerometer along with directional information from the electronic compass.

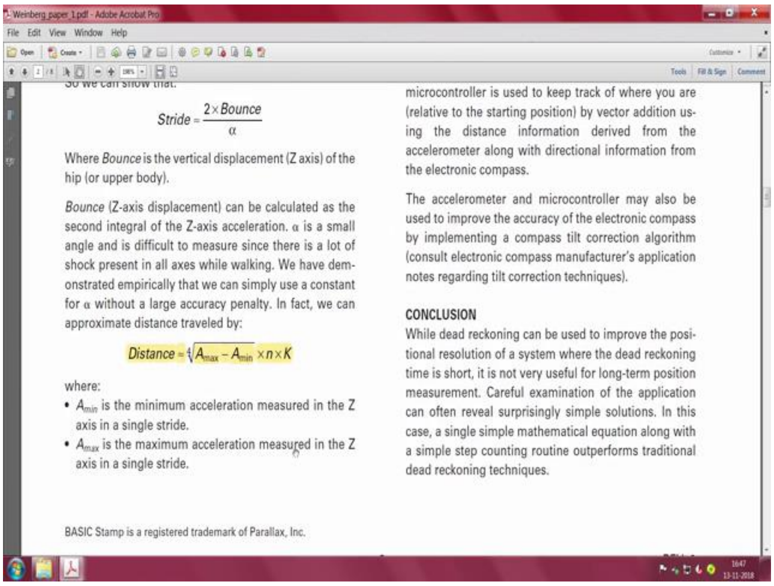
The accelerometer and microcontroller may also be used to improve the accuracy of the electronic compass by implementing a compass tilt correction algorithm (consult electronic compass manufacturer's application notes regarding tilt correction techniques).

CONCLUSION

While dead reckoning can be used to improve the positional resolution of a system where the dead reckoning time is short, it is not very useful for long-term position measurement. Careful examination of the application

And it goes on to come up with an empirical expression of how to calculate the distance. Weinberg in fact, is the person who came up with this expression which says distance is the fourth route of the acceleration maximum a_max that is the peak minus the acceleration minimum times n which is for number of steps that you take, times K which is some constant.

$$\text{Stride length} = (a\_max - a\_min)^{1/4} * n * K$$



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$$Distance = \sqrt[4]{A_{max} - A_{min}} \times n \times K$$

where:

- A_{min} is the minimum acceleration measured in the Z axis in a single stride.
- A_{max} is the maximum acceleration measured in the Z axis in a single stride.

BASIC Stamp is a registered trademark of Parallax, Inc.

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The accelerometer and microcontroller may also be used to improve the accuracy of the electronic compass by implementing a compass tilt correction algorithm (consult electronic compass manufacturer's application notes regarding tilt correction techniques).

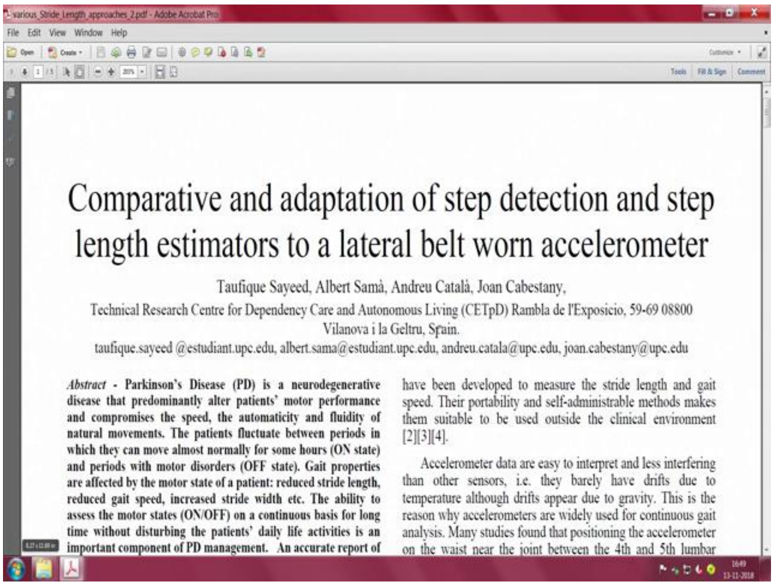
CONCLUSION

While dead reckoning can be used to improve the positional resolution of a system where the dead reckoning time is short, it is not very useful for long-term position measurement. Careful examination of the application can often reveal surprisingly simple solutions. In this case, a single simple mathematical equation along with a simple step counting routine outperforms traditional dead reckoning techniques.

The K is hard to estimate and this can differ from person to person and therefore, one may have to calibrate it for a specific person to ensure that the application that one builds is quite accurate for that particular person.

So, conclusion is that you know you could use dead reckoning to improve positional resolution of the system it is not very useful for long term position measurement although because of all these drifts and other related errors.

Careful examination of the application can often reveal surprisingly simple solution it is your ingenuity on how you want to build applications given the fact that you should not really end up with double integrals and integration accumulation error .



various_Stride_Length_approaches_2.pdf - Adobe Acrobat Pro

Comparative and adaptation of step detection and step length estimators to a lateral belt worn accelerometer

Taufique Sayeed, Albert Samà, Andreu Català, Joan Cabestany,

Technical Research Centre for Dependency Care and Autonomous Living (CETpD) Rambla de l'Exposicio, 59-69 08800 Vilanova i la Geltru, Spain.

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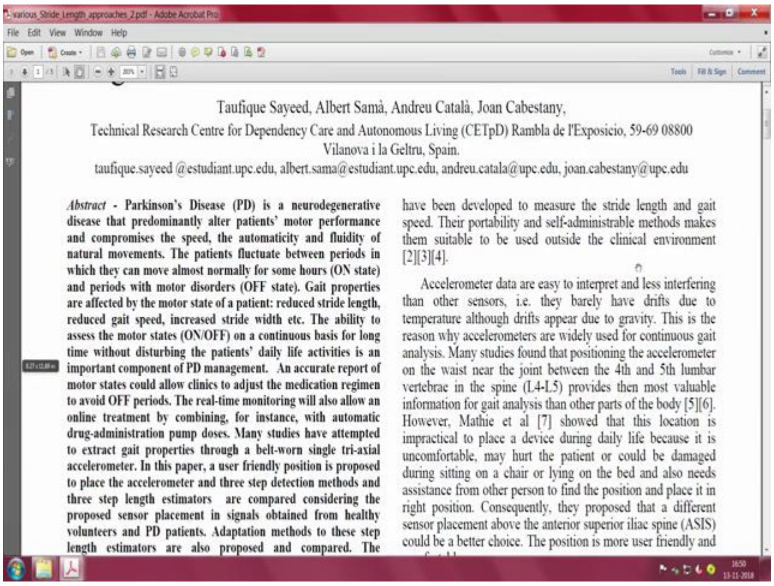
***Abstract* - Parkinson's Disease (PD) is a neurodegenerative disease that predominantly alter patients' motor performance and compromises the speed, the automaticity and fluidity of natural movements. The patients fluctuate between periods in which they can move almost normally for some hours (ON state) and periods with motor disorders (OFF state). Gait properties are affected by the motor state of a patient: reduced stride length, reduced gait speed, increased stride width etc. The ability to assess the motor states (ON/OFF) on a continuous basis for long time without disturbing the patients' daily life activities is an important component of PD management. An accurate report of**

have been developed to measure the stride length and gait speed. Their portability and self-administrable methods makes them suitable to be used outside the clinical environment [2][3][4].

Accelerometer data are easy to interpret and less interfering than other sensors, i.e. they barely have drifts due to temperature although drifts appear due to gravity. This is the reason why accelerometers are widely used for continuous gait analysis. Many studies found that positioning the accelerometer on the waist near the joint between the 4th and 5th lumbar

So, let us look at one more paper and let me give you some background of the of this paper see we are trying to do an IOT application and we are looking at localization without GPS as a broad title and we are trying to look at how to use these IMU.

The other paper which we are going to discuss actually says something even more and very specific. It says that why not use IMU s for detection of Parkinson's disease some application on Parkinson's disease. So, you have to look at also that people are already looking at use of IMU s for very specific applications. So, let us turn our attention to this paper it says comparative adaptation of the step detection and step length estimators to a lateral belt worn accelerometer the title appears very general.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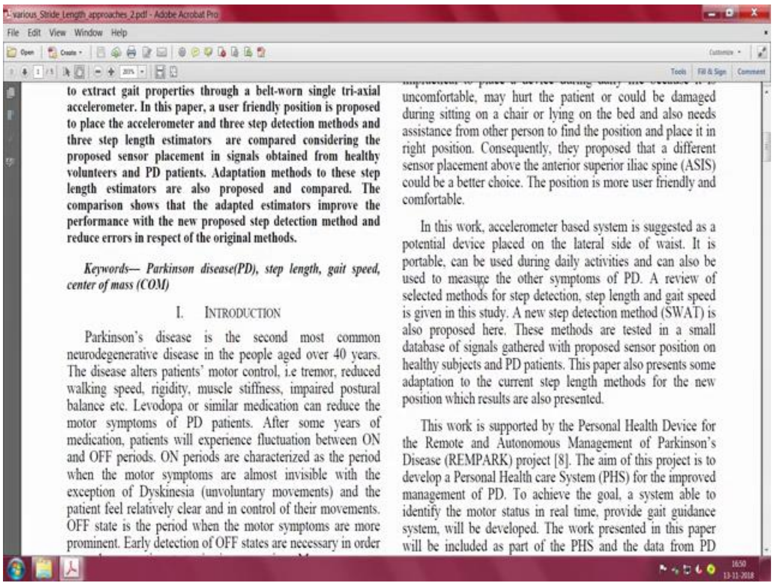
taufique.sayeed @estudiant.upc.edu, albert.sama@estudiant.upc.edu, andreu.catala@upc.edu, joan.cabestany@upc.edu

Abstract - **Parkinson's Disease (PD) is a neurodegenerative disease that predominantly alter patients' motor performance and compromises the speed, the automaticity and fluidity of natural movements. The patients fluctuate between periods in which they can move almost normally for some hours (ON state) and periods with motor disorders (OFF state). Gait properties are affected by the motor state of a patient: reduced stride length, reduced gait speed, increased stride width etc. The ability to assess the motor states (ON/OFF) on a continuous basis for long time without disturbing the patients' daily life activities is an important component of PD management. An accurate report of motor states could allow clinics to adjust the medication regimen to avoid OFF periods. The real-time monitoring will also allow an online treatment by combining, for instance, with automatic drug-administration pump doses. Many studies have attempted to extract gait properties through a belt-worn single tri-axial accelerometer. In this paper, a user friendly position is proposed to place the accelerometer and three step detection methods and three step length estimators are compared considering the proposed sensor placement in signals obtained from healthy volunteers and PD patients. Adaptation methods to these step length estimators are also proposed and compared. The**

have been developed to measure the stride length and gait speed. Their portability and self-administrable methods makes them suitable to be used outside the clinical environment [2][3][4].

Accelerometer data are easy to interpret and less interfering than other sensors, i.e. they barely have drifts due to temperature although drifts appear due to gravity. This is the reason why accelerometers are widely used for continuous gait analysis. Many studies found that positioning the accelerometer on the waist near the joint between the 4th and 5th lumbar vertebrae in the spine (L4-L5) provides then most valuable information for gait analysis than other parts of the body [5][6]. However, Mathie et al [7] showed that this location is impractical to place a device during daily life because it is uncomfortable, may hurt the patient or could be damaged during sitting on a chair or lying on the bed and also needs assistance from other person to find the position and place it in right position. Consequently, they proposed that a different sensor placement above the anterior superior iliac spine (ASIS) could be a better choice. The position is more user friendly and

But the very first line in the abstract says Parkinson's disease is a neurodegenerative disease as it predominantly alter patient's motor performance and compromises the speed and so on. So, it is actually going into the details.



to extract gait properties through a belt-worn single tri-axial accelerometer. In this paper, a user friendly position is proposed to place the accelerometer and three step detection methods and three step length estimators are compared considering the proposed sensor placement in signals obtained from healthy volunteers and PD patients. Adaptation methods to these step length estimators are also proposed and compared. The comparison shows that the adapted estimators improve the performance with the new proposed step detection method and reduce errors in respect of the original methods.

Keywords— Parkinson disease(PD), step length, gait speed, center of mass (COM)

I. INTRODUCTION

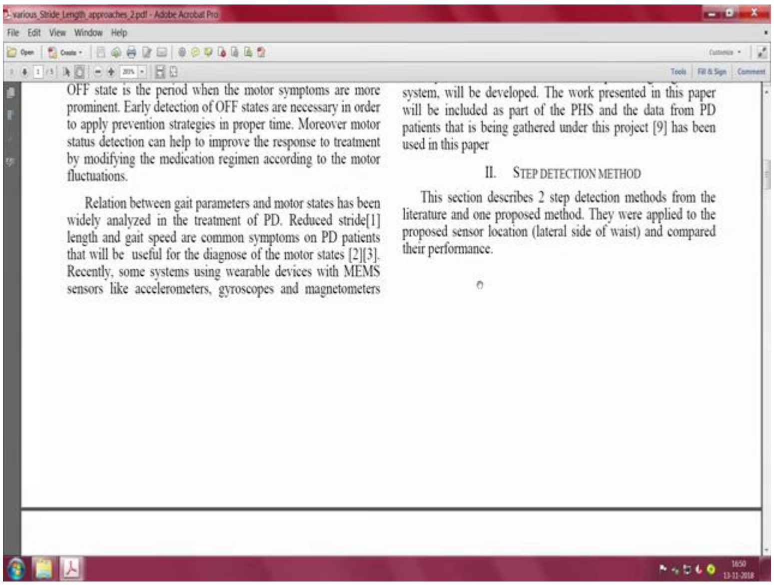
Parkinson's disease is the second most common neurodegenerative disease in the people aged over 40 years. The disease alters patients' motor control, i.e tremor, reduced walking speed, rigidity, muscle stiffness, impaired postural balance etc. Levodopa or similar medication can reduce the motor symptoms of PD patients. After some years of medication, patients will experience fluctuation between ON and OFF periods. ON periods are characterized as the period when the motor symptoms are almost invisible with the exception of Dyskinesia (unvoluntary movements) and the patient feel relatively clear and in control of their movements. OFF state is the period when the motor symptoms are more prominent. Early detection of OFF states are necessary in order

uncomfortable, may hurt the patient or could be damaged during sitting on a chair or lying on the bed and also needs assistance from other person to find the position and place it in right position. Consequently, they proposed that a different sensor placement above the anterior superior iliac spine (ASIS) could be a better choice. The position is more user friendly and comfortable.

In this work, accelerometer based system is suggested as a potential device placed on the lateral side of waist. It is portable, can be used during daily activities and can also be used to measure the other symptoms of PD. A review of selected methods for step detection, step length and gait speed is given in this study. A new step detection method (SWAT) is also proposed here. These methods are tested in a small database of signals gathered with proposed sensor position on healthy subjects and PD patients. This paper also presents some adaptation to the current step length methods for the new position which results are also presented.

This work is supported by the Personal Health Device for the Remote and Autonomous Management of Parkinson's Disease (REMPARK) project [8]. The aim of this project is to develop a Personal Health care System (PHS) for the improved management of PD. To achieve the goal, a system able to identify the motor status in real time, provide gait guidance system, will be developed. The work presented in this paper will be included as part of the PHS and the data from PD

The reason why this paper is important is because several approaches to detect steps are discussed in this paper.



OFF state is the period when the motor symptoms are more prominent. Early detection of OFF states are necessary in order to apply prevention strategies in proper time. Moreover motor status detection can help to improve the response to treatment by modifying the medication regimen according to the motor fluctuations.

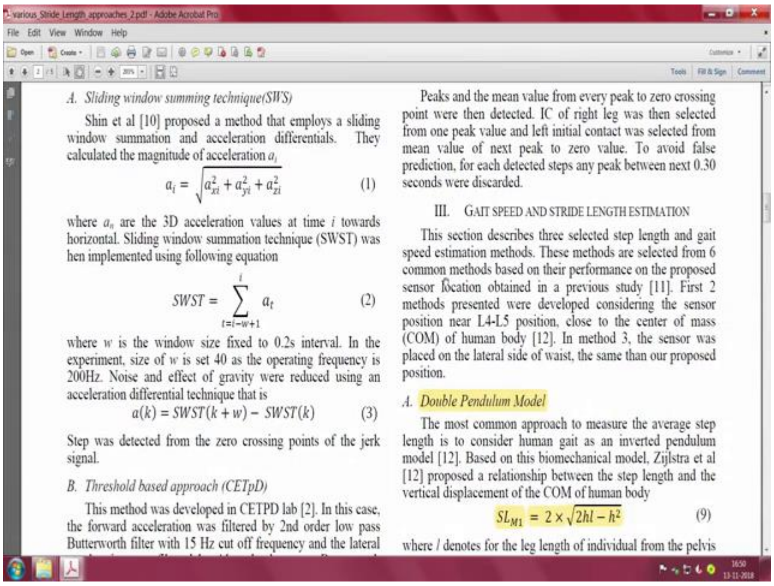
Relation between gait parameters and motor states has been widely analyzed in the treatment of PD. Reduced stride[1] length and gait speed are common symptoms on PD patients that will be useful for the diagnose of the motor states [2][3]. Recently, some systems using wearable devices with MEMS sensors like accelerometers, gyroscopes and magnetometers

system, will be developed. The work presented in this paper will be included as part of the PHS and the data from PD patients that is being gathered under this project [9] has been used in this paper

II. STEP DETECTION METHOD

This section describes 2 step detection methods from the literature and one proposed method. They were applied to the proposed sensor location (lateral side of waist) and compared their performance.

On looking at the paper we can see that sliding window summing technique is something that is proposed in this paper and there is lot of references to previous work.



A. *Sliding window summing technique(SWS)*

Shin et al [10] proposed a method that employs a sliding window summation and acceleration differentials. They calculated the magnitude of acceleration a_i

$$a_i = \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2} \qquad (1)$$

where a_{xi} are the 3D acceleration values at time i towards horizontal. Sliding window summation technique (SWST) was hen implemented using following equation

$$SWST = \sum_{t=i-w+1}^{i} a_t \qquad (2)$$

where w is the window size fixed to 0.2s interval. In the experiment, size of w is set 40 as the operating frequency is 200Hz. Noise and effect of gravity were reduced using an acceleration differential technique that is

$$a(k) = SWST(k+w) - SWST(k) \qquad (3)$$

Step was detected from the zero crossing points of the jerk signal.

B. *Threshold based approach (CETpD)*

This method was developed in CETPD lab [2]. In this case, the forward acceleration was filtered by 2nd order low pass Butterworth filter with 15 Hz cut off frequency and the lateral

Peaks and the mean value from every peak to zero crossing point were then detected. IC of right leg was then selected from one peak value and left initial contact was selected from mean value of next peak to zero value. To avoid false prediction, for each detected steps any peak between next 0.30 seconds were discarded.

III. GAIT SPEED AND STRIDE LENGTH ESTIMATION

This section describes three selected step length and gait speed estimation methods. These methods are selected from 6 common methods based on their performance on the proposed sensor location obtained in a previous study [11]. First 2 methods presented were developed considering the sensor position near L4-L5 position, close to the center of mass (COM) of human body [12]. In method 3, the sensor was placed on the lateral side of waist, the same than our proposed position.

A. *Double Pendulum Model*

The most common approach to measure the average step length is to consider human gait as an inverted pendulum model [12]. Based on this biomechanical model, Zijlstra et al [12] proposed a relationship between the step length and the vertical displacement of the COM of human body

$$SL_{M1} = 2\times\sqrt{2hl - h^2} \qquad (9)$$

where l denotes for the leg length of individual from the pelvis

At the same time the authors also want to propose their own methods and remember this is very specific to the Parkinson's disease application. So, take the basic things and start adapting to very special requirements.

Threshold based approach is one another metho, then there is a sliding window averaging technique algorithm, then gait speed and stride length estimations a bunch of algorithms again there. You look at double pendulum model the most common approach to measure average step length is to consider human gait as an inverted pendulum model. Based on biomechanical model authors propose a relationship between the step length and the vertical displacement of the COM of human body. So, you can see that.

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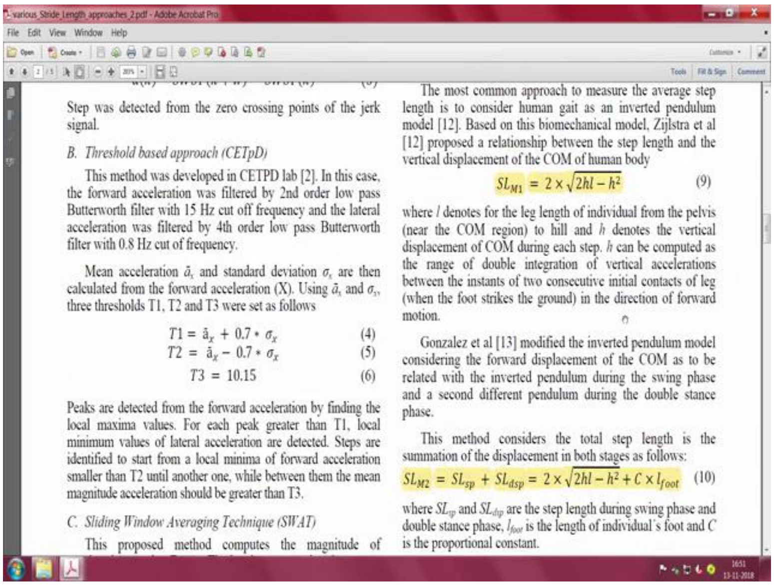


Step was detected from the zero crossing points of the jerk signal.

B. *Threshold based approach (CETpD)*

This method was developed in CETPD lab [2]. In this case, the forward acceleration was filtered by 2nd order low pass Butterworth filter with 15 Hz cut off frequency and the lateral acceleration was filtered by 4th order low pass Butterworth filter with 0.8 Hz cut of frequency.

Mean acceleration $\bar{a}_x$ and standard deviation σ_x are then calculated from the forward acceleration (X). Using $\bar{a}_x$ and σ_x, three thresholds T1, T2 and T3 were set as follows

$$T1 = \bar{a}_x + 0.7 * \sigma_x \qquad (4)$$
$$T2 = \bar{a}_x - 0.7 * \sigma_x \qquad (5)$$
$$T3 = 10.15 \qquad (6)$$

Peaks are detected from the forward acceleration by finding the local maxima values. For each peak greater than T1, local minimum values of lateral acceleration are detected. Steps are identified to start from a local minima of forward acceleration smaller than T2 until another one, while between them the mean magnitude acceleration should be greater than T3.

C. *Sliding Window Averaging Technique (SWAT)*

This proposed method computes the magnitude of

The most common approach to measure the average step length is to consider human gait as an inverted pendulum model [12]. Based on this biomechanical model, Zijlstra et al [12] proposed a relationship between the step length and the vertical displacement of the COM of human body

$$SL_{M1} = 2\times\sqrt{2hl - h^2} \qquad (9)$$

where l denotes for the leg length of individual from the pelvis (near the COM region) to hill and h denotes the vertical displacement of COM during each step. h can be computed as the range of double integration of vertical accelerations between the instants of two consecutive initial contacts of leg (when the foot strikes the ground) in the direction of forward motion.

Gonzalez et al [13] modified the inverted pendulum model considering the forward displacement of the COM as to be related with the inverted pendulum during the swing phase and a second different pendulum during the double stance phase.

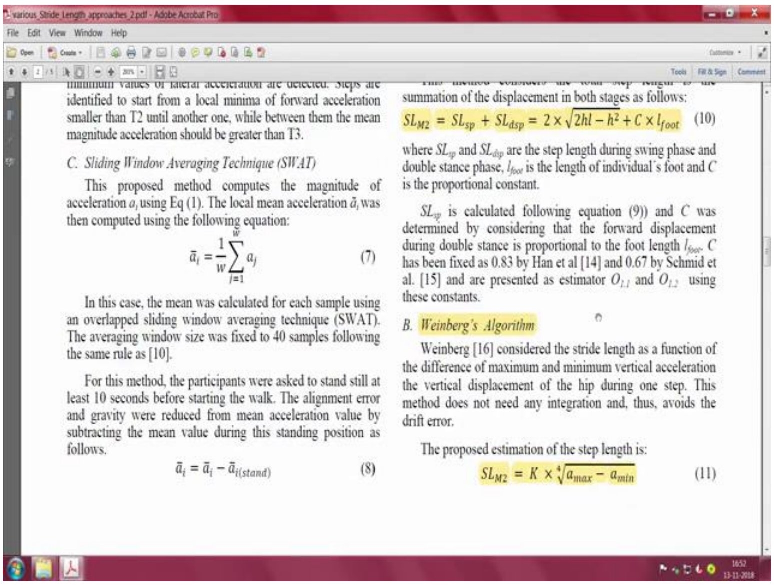
This method considers the total step length is the summation of the displacement in both stages as follows:

$$SL_{M2} = SL_{sp} + SL_{dsp} = 2\times\sqrt{2hl - h^2} + C\times l_{foot} \qquad (10)$$

where SL_{sp} and SL_{dsp} are the step length during swing phase and double stance phase, l_{foot} is the length of individual's foot and C is the proportional constant.

They talk about the almost the same thing leg length of individual from the pelvis near the COM, COM region to hill and h denotes the vertical displacement of also it is everything around the inverted pendulum the hip pelvis region that is exactly from where the vertical acceleration is being looked at.

So, we talk about the heel strike and stance, essentially 2 phases whenever we walk we will essentially relate to heel strike and stance.



minimum values of lateral acceleration are detected. Steps are identified to start from a local minima of forward acceleration smaller than T2 until another one, while between them the mean magnitude acceleration should be greater than T3.

C. *Sliding Window Averaging Technique (SWAT)*

This proposed method computes the magnitude of acceleration a_i using Eq (1). The local mean acceleration $\bar{a}_i$ was then computed using the following equation:

$$\bar{a}_i = \frac{1}{w}\sum_{j=1}^{w} a_j \quad (7)$$

In this case, the mean was calculated for each sample using an overlapped sliding window averaging technique (SWAT). The averaging window size was fixed to 40 samples following the same rule as [10].

For this method, the participants were asked to stand still at least 10 seconds before starting the walk. The alignment error and gravity were reduced from mean acceleration value by subtracting the mean value during this standing position as follows.

$$\bar{a}_i = \bar{a}_i - \bar{a}_{i(stand)} \quad (8)$$

This method considers the total step length as the summation of the displacement in both stages as follows:

$$SL_{M2} = SL_{sp} + SL_{dsp} = 2 \times \sqrt{2hl - h^2} + C \times l_{foot} \quad (10)$$

where SL_{sp} and SL_{dsp} are the step length during swing phase and double stance phase, l_{foot} is the length of individual's foot and C is the proportional constant.

SL_{sp} is calculated following equation (9)) and C was determined by considering that the forward displacement during double stance is proportional to the foot length l_{foot}. C has been fixed as 0.83 by Han et al [14] and 0.67 by Schmid et al. [15] and are presented as estimator $O_{1,1}$ and $O_{1,2}$ using these constants.

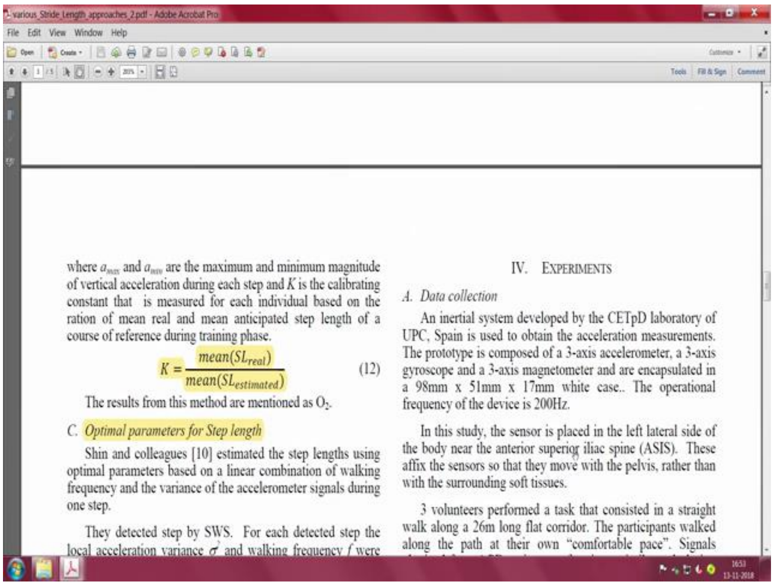
B. *Weinberg's Algorithm*

Weinberg [16] considered the stride length as a function of the difference of maximum and minimum vertical acceleration the vertical displacement of the hip during one step. This method does not need any integration and, thus, avoids the drift error.

The proposed estimation of the step length is:

$$SL_{M2} = K \times \sqrt[4]{a_{max} - a_{min}} \quad (11)$$

Then there is Weinberg's algorithm which is considered for stride length estimation of a as a function of difference in maximum and minimum vertical acceleration the vertical displacement of the hip during one step. This method does not need any integration and thus avoids drift error, you can see the strength of Weinberg which I also discussed in the previous paper is because the fact that there is no integration error.



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where a_{max} and a_{min} are the maximum and minimum magnitude of vertical acceleration during each step and K is the calibrating constant that is measured for each individual based on the ration of mean real and mean anticipated step length of a course of reference during training phase.

$$K = \frac{mean(SL_{real})}{mean(SL_{estimated})} \quad (12)$$

The results from this method are mentioned as O_2.

C. *Optimal parameters for Step length*

Shin and colleagues [10] estimated the step lengths using optimal parameters based on a linear combination of walking frequency and the variance of the accelerometer signals during one step.

They detected step by SWS. For each detected step the local acceleration variance σ^2 and walking frequency f were

IV. EXPERIMENTS

A. *Data collection*

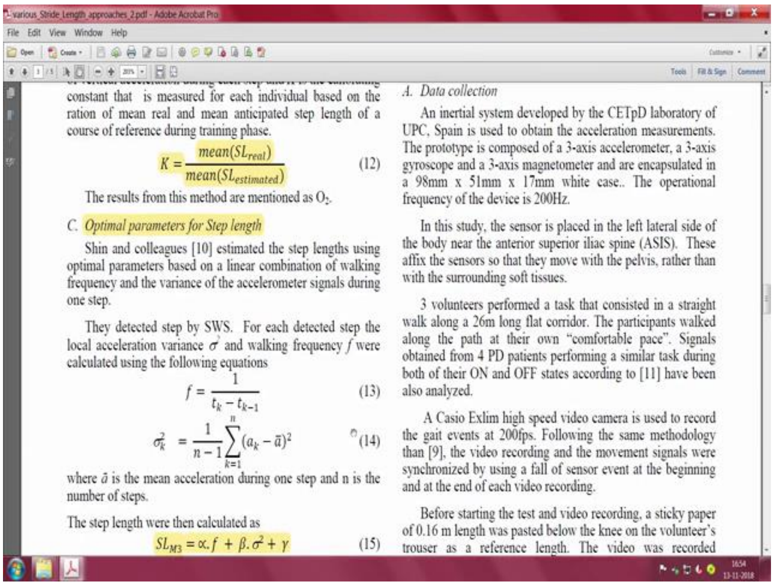
An inertial system developed by the CETpD laboratory of UPC, Spain is used to obtain the acceleration measurements. The prototype is composed of a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer and are encapsulated in a 98mm x 51mm x 17mm white case.. The operational frequency of the device is 200Hz.

In this study, the sensor is placed in the left lateral side of the body near the anterior superior iliac spine (ASIS). These affix the sensors so that they move with the pelvis, rather than with the surrounding soft tissues.

3 volunteers performed a task that consisted in a straight walk along a 26m long flat corridor. The participants walked along the path at their own "comfortable pace". Signals

So, you have to take the a_max then you have to take the a_min and then you have to keep doing it for every step. Some people adapt even averaging moving averaging of a_max and a_min some of them seem to just take the absolute value absolute value of a_max. So, many methods can exist, you should keep trying these are all variants that you yourself can try once you have the basic code with you and very exciting results can be observed.

K as I mentioned is a calibrating constant and essentially it is a ratio of the mean stride length real stride length that is there with that of the mean stride length that is estimated essentially it is just a ratio.



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The results from this method are mentioned as O_2.

C. *Optimal parameters for Step length*

Shin and colleagues [10] estimated the step lengths using optimal parameters based on a linear combination of walking frequency and the variance of the accelerometer signals during one step.

They detected step by SWS. For each detected step the local acceleration variance σ^2 and walking frequency f were calculated using the following equations

$$f = \frac{1}{t_k - t_{k-1}} \quad (13)$$

$$\sigma_k^2 = \frac{1}{n-1}\sum_{k=1}^{n}(a_k - \bar{a})^2 \quad (14)$$

where $\bar{a}$ is the mean acceleration during one step and n is the number of steps.

The step length were then calculated as

$$SL_{M3} = \alpha.f + \beta.\sigma^2 + \gamma \quad (15)$$

A. *Data collection*

An inertial system developed by the CETpD laboratory of UPC, Spain is used to obtain the acceleration measurements. The prototype is composed of a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer and are encapsulated in a 98mm x 51mm x 17mm white case.. The operational frequency of the device is 200Hz.

In this study, the sensor is placed in the left lateral side of the body near the anterior superior iliac spine (ASIS). These affix the sensors so that they move with the pelvis, rather than with the surrounding soft tissues.

3 volunteers performed a task that consisted in a straight walk along a 26m long flat corridor. The participants walked along the path at their own "comfortable pace". Signals obtained from 4 PD patients performing a similar task during both of their ON and OFF states according to [11] have been also analyzed.

A Casio Exlim high speed video camera is used to record the gait events at 200fps. Following the same methodology than [9], the video recording and the movement signals were synchronized by using a fall of sensor event at the beginning and at the end of each video recording.

Before starting the test and video recording, a sticky paper of 0.16 m length was pasted below the knee on the volunteer's trouser as a reference length. The video was recorded

So, then there are optimal parameters that this authors talk about for step length and other methods.

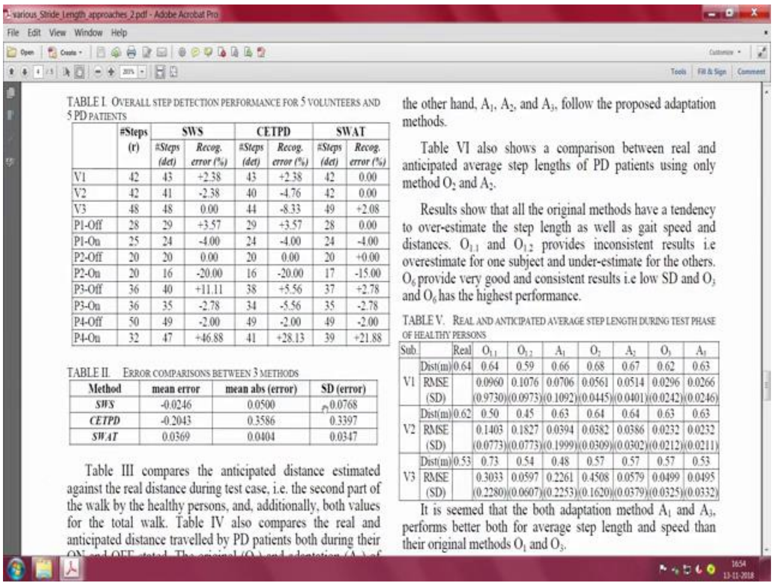

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TABLE I. OVERALL STEP DETECTION PERFORMANCE FOR 5 VOLUNTEERS AND 5 PD PATIENTS

	#Steps (r)	SWS		CETPD		SWAT	
		#Steps (det)	Recog. error (%)	#Steps (det)	Recog. error (%)	#Steps (det)	Recog. error (%)
V1	42	43	+2.38	43	+2.38	42	0.00
V2	42	41	-2.38	40	-4.76	42	0.00
V3	48	48	0.00	44	-8.33	49	+2.08
P1-Off	28	29	+3.57	29	+3.57	28	0.00
P1-On	25	24	-4.00	24	-4.00	24	-4.00
P2-Off	20	20	0.00	20	0.00	20	+0.00
P2-On	20	16	-20.00	16	-20.00	17	-15.00
P3-Off	36	40	+11.11	38	+5.56	37	+2.78
P3-On	36	35	-2.78	34	-5.56	35	-2.78
P4-Off	50	49	-2.00	49	-2.00	49	-2.00
P4-On	32	47	+46.88	41	+28.13	39	+21.88

TABLE II. ERROR COMPARISONS BETWEEN 3 METHODS

Method	mean error	mean abs (error)	SD (error)
SWS	-0.0246	0.0500	0.0768
CETPD	-0.2043	0.3586	0.3397
SWAT	0.0369	0.0404	0.0347

Table III compares the anticipated distance estimated against the real distance during test case, i.e. the second part of the walk by the healthy persons, and, additionally, both values for the total walk. Table IV also compares the real and anticipated distance travelled by PD patients both during their

the other hand, A_1, A_2, and A_3, follow the proposed adaptation methods.

Table VI also shows a comparison between real and anticipated average step lengths of PD patients using only method O_2 and A_2.

Results show that all the original methods have a tendency to over-estimate the step length as well as gait speed and distances. $O_{1.1}$ and $O_{1.2}$ provides inconsistent results i.e overestimate for one subject and under-estimate for the others. O_6 provide very good and consistent results i.e low SD and O_3 and O_6 has the highest performance.

TABLE V. REAL AND ANTICIPATED AVERAGE STEP LENGTH DURING TEST PHASE OF HEALTHY PERSONS

Sub.		Real	$O_{1.1}$	$O_{1.2}$	A_1	O_2	A_2	O_3	A_3
V1	Dist(m)	0.64	0.64	0.59	0.66	0.68	0.67	0.62	0.63
	RMSE (SD)		0.0960 (0.9730)	0.1076 (0.0973)	0.0706 (0.1092)	0.0561 (0.0445)	0.0514 (0.0401)	0.0296 (0.0242)	0.0266 (0.0246)
V2	Dist(m)	0.62	0.50	0.45	0.63	0.64	0.64	0.63	0.63
	RMSE (SD)		0.1403 (0.0773)	0.1827 (0.0773)	0.0394 (0.1999)	0.0382 (0.0309)	0.0386 (0.0302)	0.0232 (0.0212)	0.0232 (0.0211)
V3	Dist(m)	0.53	0.73	0.54	0.48	0.57	0.57	0.57	0.53
	RMSE (SD)		0.3033 (0.2280)	0.0597 (0.0607)	0.2261 (0.2253)	0.4508 (0.1620)	0.0579 (0.0379)	0.0499 (0.0325)	0.0495 (0.0332)

It is seemed that the both adaptation method A_1 and A_3, performs better both for average step length and speed than their original methods O_1 and O_3.

And then they have some results associated with this particular application which essentially you should look at in for the Parkinson’s disease case.

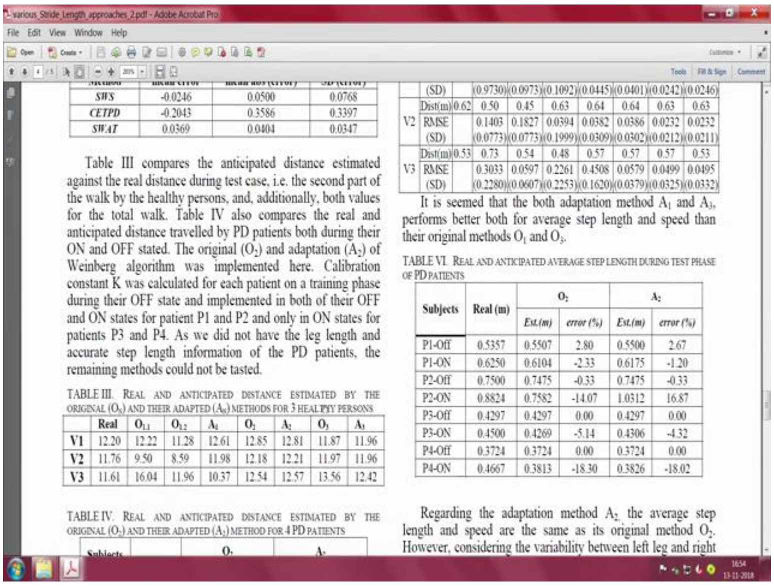

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Table III compares the anticipated distance estimated against the real distance during test case, i.e. the second part of the walk by the healthy persons, and, additionally, both values for the total walk. Table IV also compares the real and anticipated distance travelled by PD patients both during their ON and OFF stated. The original (O_2) and adaptation (A_2) of Weinberg algorithm was implemented here. Calibration constant K was calculated for each patient on a training phase during their OFF state and implemented in both of their OFF and ON states for patient P1 and P2 and only in ON states for patients P3 and P4. As we did not have the leg length and accurate step length information of the PD patients, the remaining methods could not be tasted.

TABLE III. REAL AND ANTICIPATED DISTANCE ESTIMATED BY THE ORIGINAL (O_X) AND THEIR ADAPTED (A_X) METHODS FOR 3 HEALTHY PERSONS

	Real	$O_{1.1}$	$O_{1.2}$	A_1	O_2	A_2	O_3	A_3
V1	12.20	12.22	11.28	12.61	12.85	12.81	11.87	11.96
V2	11.76	9.50	8.59	11.98	12.18	12.21	11.97	11.96
V3	11.61	16.04	11.96	10.37	12.54	12.57	13.56	12.42

TABLE IV. REAL AND ANTICIPATED DISTANCE ESTIMATED BY THE ORIGINAL (O_2) AND THEIR ADAPTED (A_2) METHOD FOR 4 PD PATIENTS

Subjects		O_2	A_2

	(SD)		(0.9730)	(0.0973)	(0.1092)	(0.0445)	(0.0401)	(0.0242)	(0.0246)
V2	Dist(m)	0.62	0.50	0.45	0.63	0.64	0.64	0.63	0.63
	RMSE (SD)		0.1403 (0.0773)	0.1827 (0.0773)	0.0394 (0.1999)	0.0382 (0.0309)	0.0386 (0.0302)	0.0232 (0.0212)	0.0232 (0.0211)
V3	Dist(m)	0.53	0.73	0.54	0.48	0.57	0.57	0.57	0.53
	RMSE (SD)		0.3033 (0.2280)	0.0597 (0.0607)	0.2261 (0.2253)	0.4508 (0.1620)	0.0579 (0.0379)	0.0499 (0.0325)	0.0495 (0.0332)

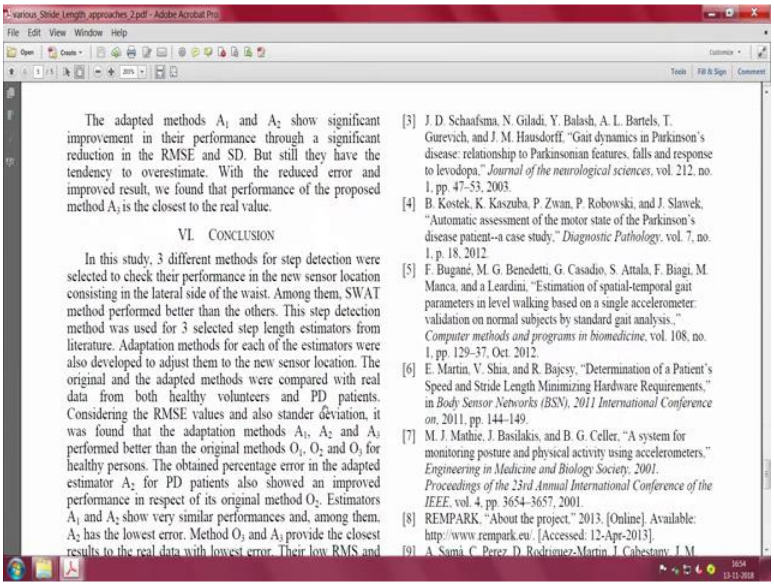
It is seemed that the both adaptation method A_1 and A_3, performs better both for average step length and speed than their original methods O_1 and O_3.

TABLE VI. REAL AND ANTICIPATED AVERAGE STEP LENGTH DURING TEST PHASE OF PD PATIENTS

Subjects	Real (m)	O_2		A_2	
		Est.(m)	error (%)	Est.(m)	error (%)
P1-Off	0.5357	0.5507	2.80	0.5500	2.67
P1-ON	0.6250	0.6104	-2.33	0.6175	-1.20
P2-Off	0.7500	0.7475	-0.33	0.7475	-0.33
P2-ON	0.8824	0.7582	-14.07	1.0312	16.87
P3-Off	0.4297	0.4297	0.00	0.4297	0.00
P3-ON	0.4500	0.4269	-5.14	0.4306	-4.32
P4-Off	0.3724	0.3724	0.00	0.3724	0.00
P4-ON	0.4667	0.3813	-18.30	0.3826	-18.02

Regarding the adaptation method A_2, the average step length and speed are the same as its original method O_2. However, considering the variability between left leg and right

So, they have some results they present these results.



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The adapted methods A_1 and A_2 show significant improvement in their performance through a significant reduction in the RMSE and SD. But still they have the tendency to overestimate. With the reduced error and improved result, we found that performance of the proposed method A_3 is the closest to the real value.

VI. CONCLUSION

In this study, 3 different methods for step detection were selected to check their performance in the new sensor location consisting in the lateral side of the waist. Among them, SWAT method performed better than the others. This step detection method was used for 3 selected step length estimators from literature. Adaptation methods for each of the estimators were also developed to adjust them to the new sensor location. The original and the adapted methods were compared with real data from both healthy volunteers and PD patients. Considering the RMSE values and also stander deviation, it was found that the adaptation methods A_1, A_2 and A_3 performed better than the original methods O_1, O_2 and O_3 for healthy persons. The obtained percentage error in the adapted estimator A_2 for PD patients also showed an improved performance in respect of its original method O_2. Estimators A_1 and A_2 show very similar performances and, among them, A_2 has the lowest error. Method O_3 and A_3 provide the closest results to the real data with lowest error. Their low RMS and

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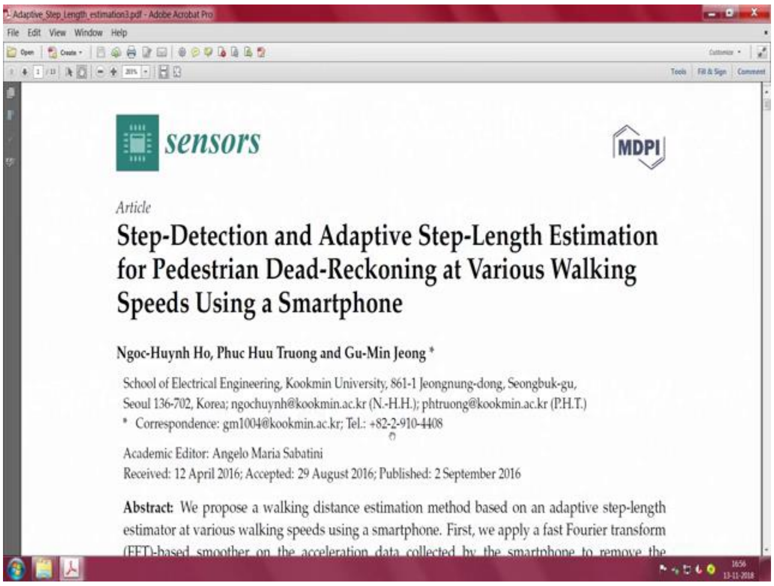
And essentially they talk about the 3 different methods for step detection and their associated performances, then strength and weakness assessments, sensor location where should you put and then there are also step length estimations estimators 3 selected step length estimators from literature they look up then adaptation methods for each of the estimators.

So, in summary this is an interesting paper also because it sort of gives you an overview of how active this area is.



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Article

Step-Detection and Adaptive Step-Length Estimation for Pedestrian Dead-Reckoning at Various Walking Speeds Using a Smartphone

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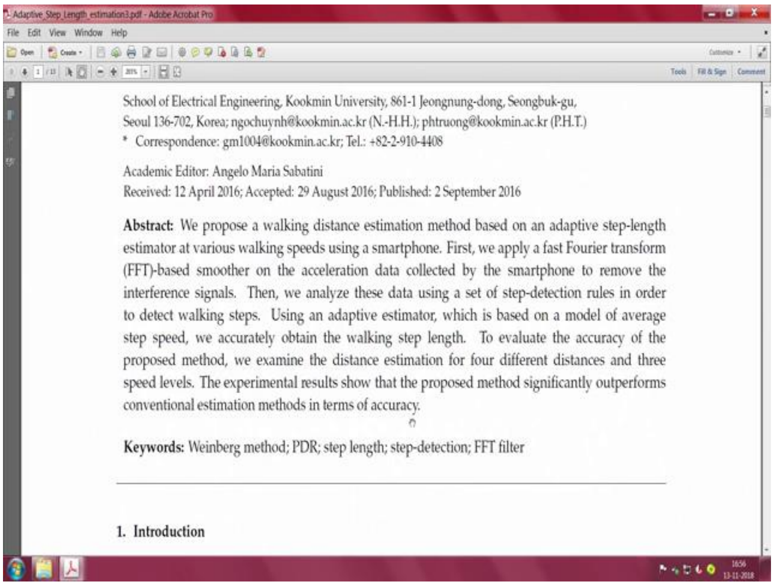
Academic Editor: Angelo Maria Sabatini
Received: 12 April 2016; Accepted: 29 August 2016; Published: 2 September 2016

Abstract: We propose a walking distance estimation method based on an adaptive step-length estimator at various walking speeds using a smartphone. First, we apply a fast Fourier transform (FFT)-based smoother on the acceleration data collected by the smartphone to remove the

Ok so, I will take you to one more paper which is talking about step detection and adaptive step length estimation for pedestrian dead reckoning at various walking speeds using a Smartphone.

Essentially, what we have been talking of with respect to use of IMU's, this paper is also equally good and as you can see they are looking at adaptive step length estimation.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Abstract: We propose a walking distance estimation method based on an adaptive step-length estimator at various walking speeds using a smartphone. First, we apply a fast Fourier transform (FFT)-based smoother on the acceleration data collected by the smartphone to remove the interference signals. Then, we analyze these data using a set of step-detection rules in order to detect walking steps. Using an adaptive estimator, which is based on a model of average step speed, we accurately obtain the walking step length. To evaluate the accuracy of the proposed method, we examine the distance estimation for four different distances and three speed levels. The experimental results show that the proposed method significantly outperforms conventional estimation methods in terms of accuracy.

Keywords: Weinberg method; PDR; step length; step-detection; FFT filter

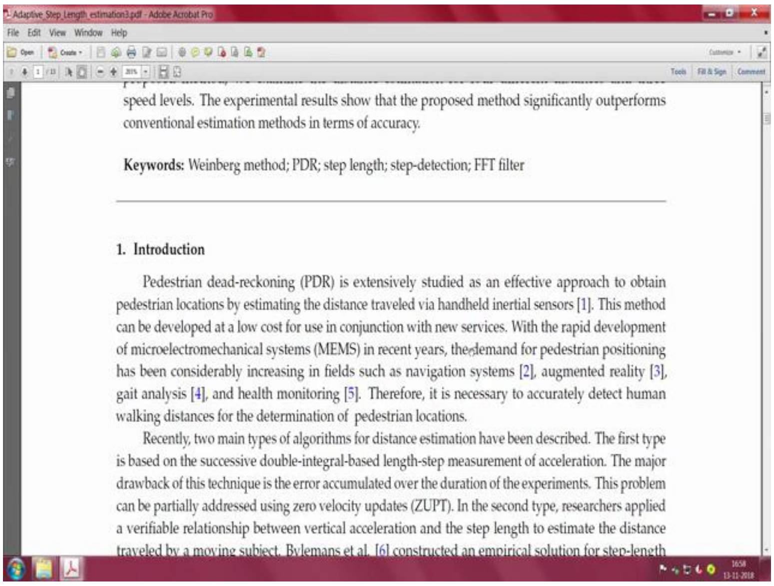
1. Introduction

While this paper is interesting, they also have some nice ideas in this and I found this to be a nice thing. Let us read the abstract and you will essentially get a very good idea. I mentioned to you in one of the previous slides about getting raw accelerometer data and then applying a filter right. Now we could be applying as I said different orders of filters then you can have one of them which is quite popular is indeed the Butterworth filters. Here in this paper, they do it differently what they do is they do a FFT and then they do an inverse FFT back and that is purely for the purpose of noise removal.

We will see those results also. So, you can also apply FFT and inverse FFT to smoothen the raw values that you get so, that is a interesting. So, there is application of Lagrange multiplier and all that so, you can have a look at that. So, let us read the abstract this adaptive side length estimator for various walking speeds. So, you can see we apply FFT fast Fourier transform smoothening for the data that you collect, then we analyze this data set for step detection rules in order to detect walking steps and then there is an adaptive estimator which is based on the model of average step speed we accurately obtain the walking step length.

To evaluate the accuracy of the proposed method we examine the distance estimation for 4 different distances and 3 speed levels, as usual claim is that the experimental result show the proposed method significantly outperforms conventional estimation methods.

So, what is the key take away from this paper, this point adaptive estimator is what they use which is based on the model of average step speed. So, they have to use the average step speed in order to accurately obtain the walking step length this is the big take away from the paper.



speed levels. The experimental results show that the proposed method significantly outperforms conventional estimation methods in terms of accuracy.

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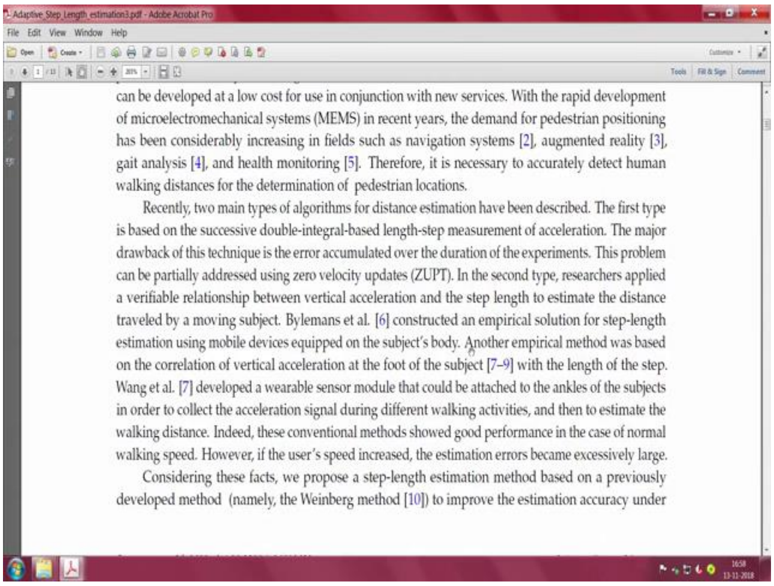
1. **Introduction**

Pedestrian dead-reckoning (PDR) is extensively studied as an effective approach to obtain pedestrian locations by estimating the distance traveled via handheld inertial sensors [1]. This method can be developed at a low cost for use in conjunction with new services. With the rapid development of microelectromechanical systems (MEMS) in recent years, the demand for pedestrian positioning has been considerably increasing in fields such as navigation systems [2], augmented reality [3], gait analysis [4], and health monitoring [5]. Therefore, it is necessary to accurately detect human walking distances for the determination of pedestrian locations.

Recently, two main types of algorithms for distance estimation have been described. The first type is based on the successive double-integral-based length-step measurement of acceleration. The major drawback of this technique is the error accumulated over the duration of the experiments. This problem can be partially addressed using zero velocity updates (ZUPT). In the second type, researchers applied a verifiable relationship between vertical acceleration and the step length to estimate the distance



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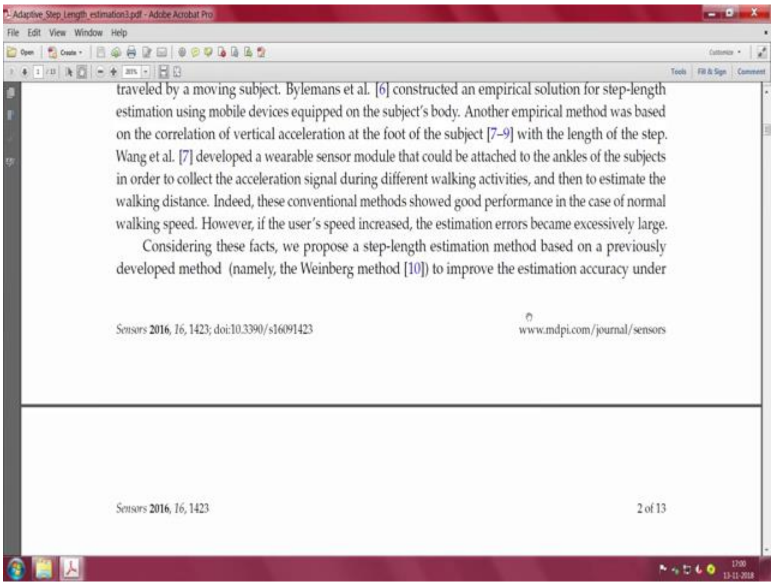
Considering these facts, we propose a step-length estimation method based on a previously developed method (namely, the Weinberg method [10]) to improve the estimation accuracy under

Lets examine this second paragraph here two main algorithms for distance estimation, the first one is successive double integral based step length measurement of acceleration. We have discussed this enough now you know that double integral based is not so good.

The major drawback is error accumulated over the duration and how does one correct it there is a method you do 0 velocity updates ZUPT and while doing ZUPT you could essentially get rid of this to minimize I would say not get rid of will be able to minimize the accumulated error.

Now, the second type where researchers are looking at is do not do double integration at all. You have a verifiable relationship between vertical acceleration which is nothing, but yaw which is nothing, but Z which is nothing, but what I showed you in this phone moving up and down this is yaw this is nothing, but vertical acceleration this is nothing, but Z axis all are the same. you keep that in mind and as we read we will understand them further.

Vertical acceleration and the step length to estimate the distance travelled by a moving subject. So, this is so, then you have empirical solutions for step length estimation using mobile many many people have worked on it and they describe all the nice work that has gone behind.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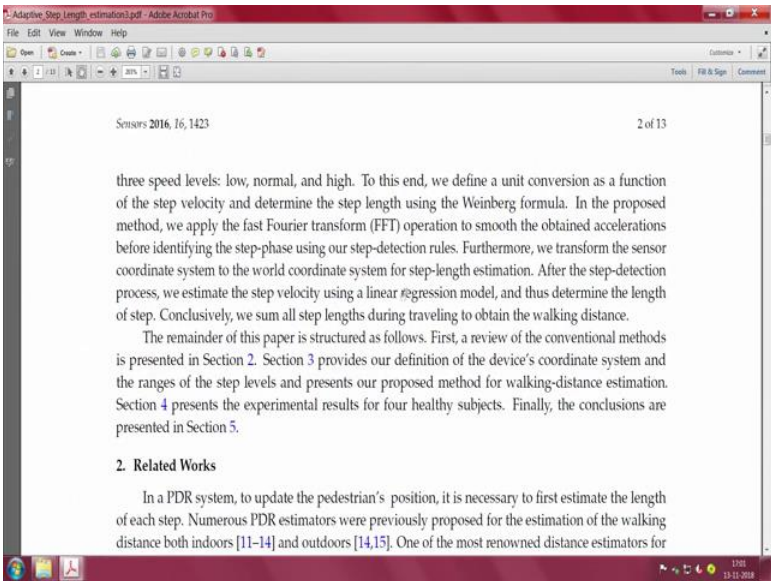
So, considering many things many problems that are there so, this step length estimation method based on previously developed method. Particularly Weinberg.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three speed levels: low, normal, and high. To this end, we define a unit conversion as a function of the step velocity and determine the step length using the Weinberg formula. In the proposed method, we apply the fast Fourier transform (FFT) operation to smooth the obtained accelerations before identifying the step-phase using our step-detection rules. Furthermore, we transform the sensor coordinate system to the world coordinate system for step-length estimation. After the step-detection process, we estimate the step velocity using a linear regression model, and thus determine the length of step. Conclusively, we sum all step lengths during traveling to obtain the walking distance.

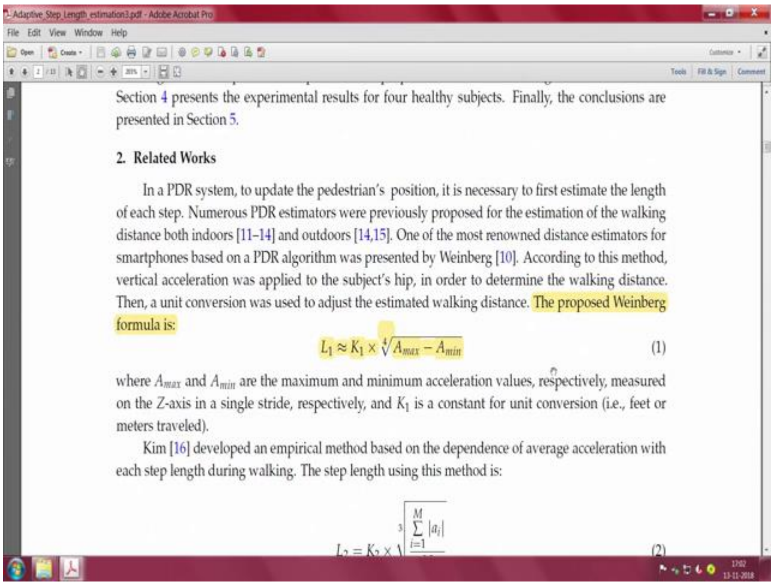
The remainder of this paper is structured as follows. First, a review of the conventional methods is presented in Section 2. Section 3 provides our definition of the device's coordinate system and the ranges of the step levels and presents our proposed method for walking-distance estimation. Section 4 presents the experimental results for four healthy subjects. Finally, the conclusions are presented in Section 5.

2. Related Works

In a PDR system, to update the pedestrian's position, it is necessary to first estimate the length of each step. Numerous PDR estimators were previously proposed for the estimation of the walking distance both indoors [11–14] and outdoors [14,15]. One of the most renowned distance estimators for

Considering these facts, we propose a step length estimation method based on previously developed method to improve the estimation accuracy under the 3 speed levels of low, normal and high. Essentially it is also using the Weinberg expression and improving up on the Weinberg expression, to this end we define a unit conversion of step velocity and determine the step length using Weinberg formula and you can see that they do FFT operation to smooth the obtained accelerations before identifying the step phase using our step detection rules.

Then they transform the sensor coordinate system to the world coordinate system for step length estimation right and after the step length process. We estimate the step velocity they use a linear regression model and does determine the length of the step. Conclusively we sum up, sum all step lengths during travelling to obtain the walking distance. So, in summary even before you want to completely read this paper, this is what this paper capture.



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2. Related Works

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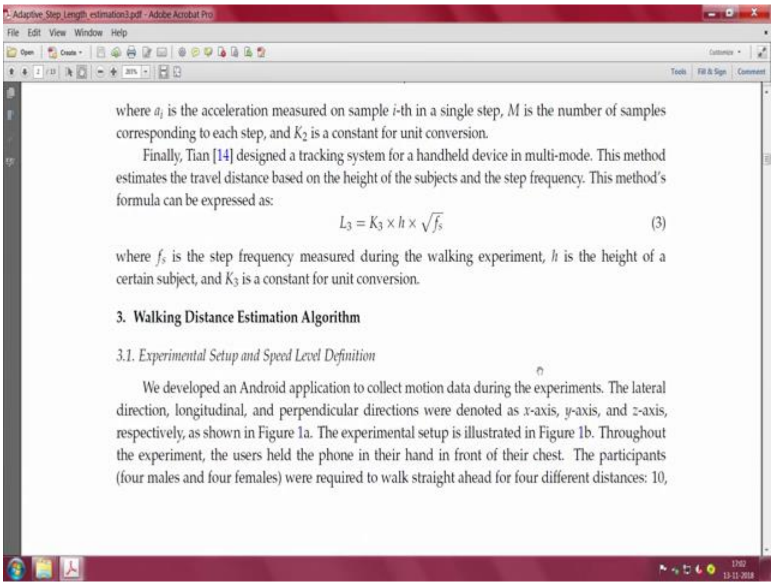
$$L_1 \approx K_1 \times \sqrt[4]{A_{max} - A_{min}} \quad (1)$$

where A_{max} and A_{min} are the maximum and minimum acceleration values, respectively, measured on the Z-axis in a single stride, respectively, and K_1 is a constant for unit conversion (i.e., feet or meters traveled).

Kim [16] developed an empirical method based on the dependence of average acceleration with each step length during walking. The step length using this method is:

$$L_2 = K_2 \times \sqrt[3]{\sum_{i=1}^{M} |a_i| \ldots} \quad (2)$$

So, all the related works are mentioned here you can see that the proposed Weinberg formula is this.



where a_i is the acceleration measured on sample i-th in a single step, M is the number of samples corresponding to each step, and K_2 is a constant for unit conversion.

Finally, Tian [14] designed a tracking system for a handheld device in multi-mode. This method estimates the travel distance based on the height of the subjects and the step frequency. This method's formula can be expressed as:

$$L_3 = K_3 \times h \times \sqrt{f_s} \quad (3)$$

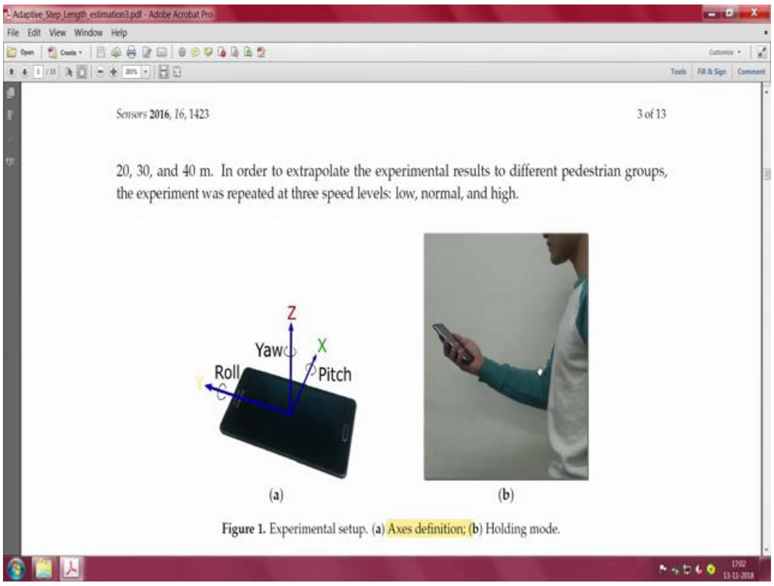
where f_s is the step frequency measured during the walking experiment, h is the height of a certain subject, and K_3 is a constant for unit conversion.

3. Walking Distance Estimation Algorithm

3.1. Experimental Setup and Speed Level Definition

We developed an Android application to collect motion data during the experiments. The lateral direction, longitudinal, and perpendicular directions were denoted as x-axis, y-axis, and z-axis, respectively, as shown in Figure 1a. The experimental setup is illustrated in Figure 1b. Throughout the experiment, the users held the phone in their hand in front of their chest. The participants (four males and four females) were required to walk straight ahead for four different distances: 10,

And walking distance estimation is what they are trying to get to and then they have an experimental set up which they talk about.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20, 30, and 40 m. In order to extrapolate the experimental results to different pedestrian groups, the experiment was repeated at three speed levels: low, normal, and high.

(a) (b)

Figure 1. Experimental setup. (a) Axes definition; (b) Holding mode.

You can see that Z is nothing, but yaw it is moving up and down and what they do is, to in order to do this experiment they actually tie the accelerometer to the leg and this is very very important because they really want to get to proper ground truthing.

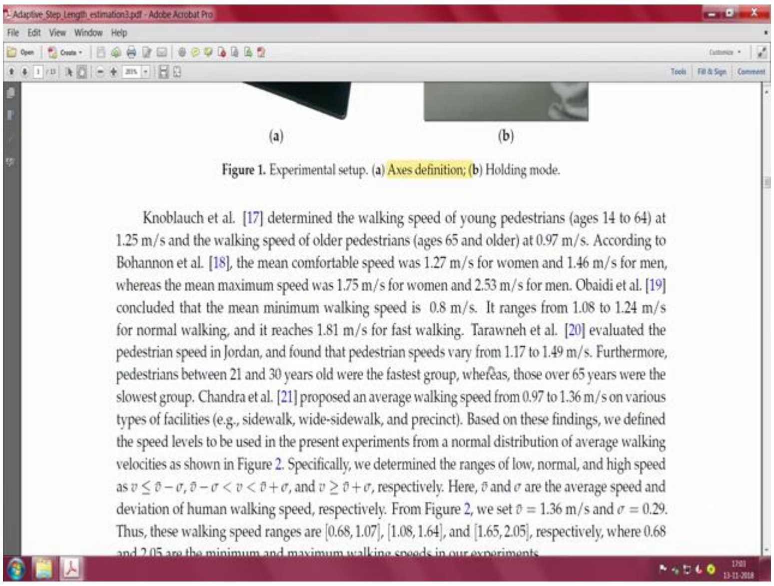
(a) (b)

Figure 1. Experimental setup. (a) Axes definition; (b) Holding mode.

Knoblauch et al. [17] determined the walking speed of young pedestrians (ages 14 to 64) at 1.25 m/s and the walking speed of older pedestrians (ages 65 and older) at 0.97 m/s. According to Bohannon et al. [18], the mean comfortable speed was 1.27 m/s for women and 1.46 m/s for men, whereas the mean maximum speed was 1.75 m/s for women and 2.53 m/s for men. Obaidi et al. [19] concluded that the mean minimum walking speed is 0.8 m/s. It ranges from 1.08 to 1.24 m/s for normal walking, and it reaches 1.81 m/s for fast walking. Tarawneh et al. [20] evaluated the pedestrian speed in Jordan, and found that pedestrian speeds vary from 1.17 to 1.49 m/s. Furthermore, pedestrians between 21 and 30 years old were the fastest group, whereas, those over 65 years were the slowest group. Chandra et al. [21] proposed an average walking speed from 0.97 to 1.36 m/s on various types of facilities (e.g., sidewalk, wide-sidewalk, and precinct). Based on these findings, we defined the speed levels to be used in the present experiments from a normal distribution of average walking velocities as shown in Figure 2. Specifically, we determined the ranges of low, normal, and high speed as $v \le \bar{v} - \sigma$, $\bar{v} - \sigma < v < \bar{v} + \sigma$, and $v \ge \bar{v} + \sigma$, respectively. Here, $\bar{v}$ and σ are the average speed and deviation of human walking speed, respectively. From Figure 2, we set $\bar{v} = 1.36$ m/s and $\sigma = 0.29$. Thus, these walking speed ranges are [0.68, 1.07], [1.08, 1.64], and [1.65, 2.05], respectively, where 0.68 and 2.05 are the minimum and maximum walking speeds in our experiments.

And this view, this paragraph is really very good if you follow this you will understand as something very nicely written here for instance, if you take young guys. What is their speed at which they walk 14 to 64 walk about 1.25 meters per second. Older people older pedestrians 65 and above go roughly 90.97 meters roughly 1 meter per second and therefore, there is according to some other observations, mean comfortable speed is about 1.27 meters per second for women and 1.46 meters per second for men. And whereas, the mean maximum speed is 1.75 meters per second for women and 2.53

meters per second for men, you plot all this and then you look at other studies that have been done and you start plotting you will get this nice average human walking speed which is on the x axis, nice histogram that you can actually plot.

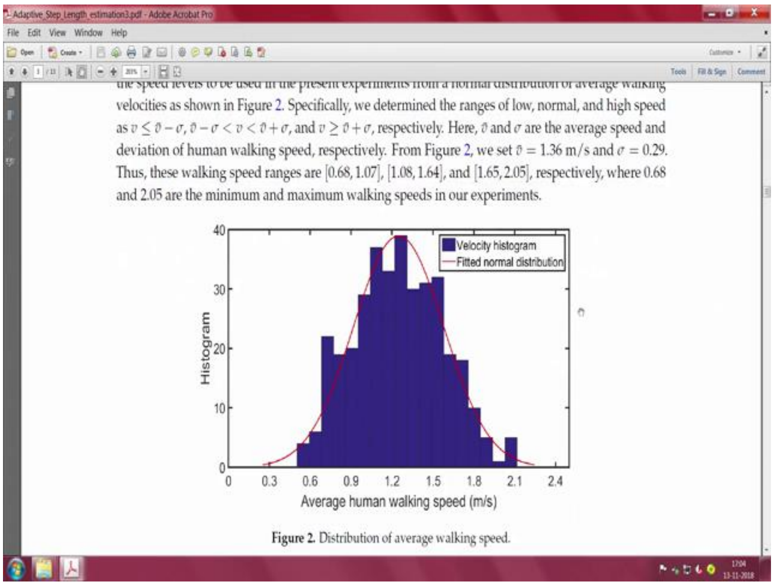
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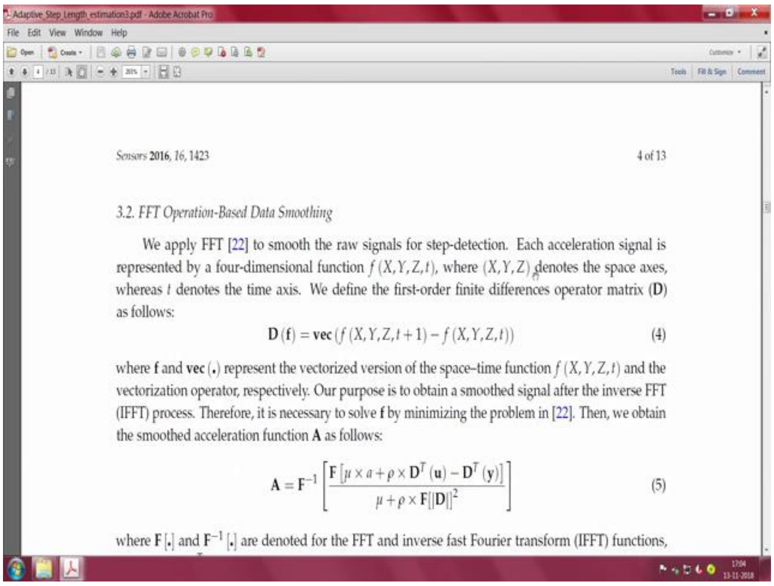
Figure 2. Distribution of average walking speed.

And then you will see that you can set the v bar which is nothing, but the average velocity to about 1.36 meters per second with a sigma which is nothing, but a deviation of human walking speed is about 0.29. So, you can see this and then they start using this basic data for all their further characterizations.

So it is a really well written paper.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3.2. FFT Operation-Based Data Smoothing

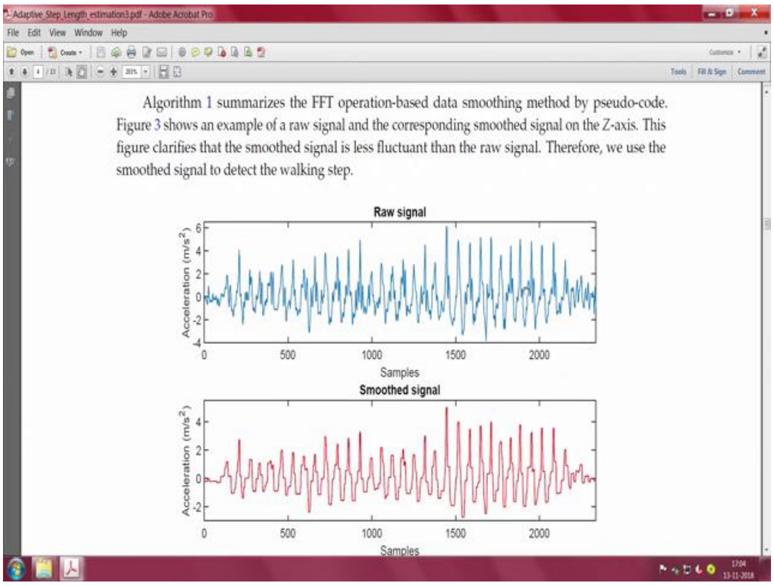
We apply FFT [22] to smooth the raw signals for step-detection. Each acceleration signal is represented by a four-dimensional function $f(X, Y, Z, t)$, where (X, Y, Z) denotes the space axes, whereas t denotes the time axis. We define the first-order finite differences operator matrix ($\mathbf{D}$) as follows:

$$\mathbf{D}(\mathbf{f}) = \mathbf{vec}\left(f(X, Y, Z, t+1) - f(X, Y, Z, t)\right) \quad (4)$$

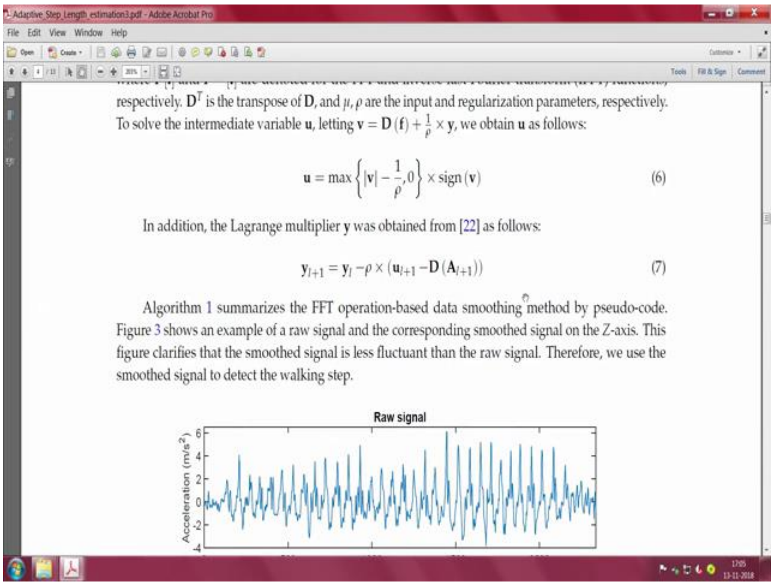
where $\mathbf{f}$ and $\mathbf{vec}(.)$ represent the vectorized version of the space–time function $f(X, Y, Z, t)$ and the vectorization operator, respectively. Our purpose is to obtain a smoothed signal after the inverse FFT (IFFT) process. Therefore, it is necessary to solve $\mathbf{f}$ by minimizing the problem in [22]. Then, we obtain the smoothed acceleration function $\mathbf{A}$ as follows:

$$\mathbf{A} = \mathbf{F}^{-1}\left[\frac{\mathbf{F}\left[\mu \times a + \rho \times \mathbf{D}^T(\mathbf{u}) - \mathbf{D}^T(\mathbf{y})\right]}{\mu + \rho \times \mathbf{F}[|\mathbf{D}|]^2}\right] \quad (5)$$

where $\mathbf{F}[.]$ and $\mathbf{F}^{-1}[.]$ are denoted for the FFT and inverse fast Fourier transform (IFFT) functions, They do FFT for data smoothening you can go through this in detail, but what is interesting is this.


Algorithm 1 summarizes the FFT operation-based data smoothing method by pseudo-code. Figure 3 shows an example of a raw signal and the corresponding smoothed signal on the Z-axis. This figure clarifies that the smoothed signal is less fluctuant than the raw signal. Therefore, we use the smoothed signal to detect the walking step.

Look at the top picture which is the raw signal and look at the smoothened signal after you do FFT, you then go back and do an inverse FFT.


respectively. $\mathbf{D}^T$ is the transpose of $\mathbf{D}$, and μ, ρ are the input and regularization parameters, respectively. To solve the intermediate variable $\mathbf{u}$, letting $\mathbf{v} = \mathbf{D}(\mathbf{f}) + \frac{1}{\rho} \times \mathbf{y}$, we obtain $\mathbf{u}$ as follows:

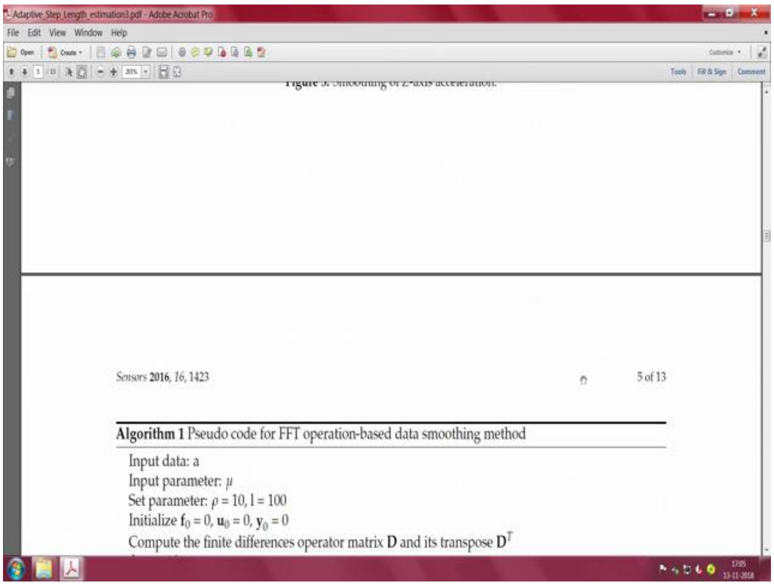
$$\mathbf{u} = \max\left\{|\mathbf{v}| - \frac{1}{\rho}, 0\right\} \times \operatorname{sign}(\mathbf{v}) \qquad (6)$$

In addition, the Lagrange multiplier $\mathbf{y}$ was obtained from [22] as follows:

$$\mathbf{y}_{l+1} = \mathbf{y}_l - \rho \times (\mathbf{u}_{l+1} - \mathbf{D}(\mathbf{A}_{l+1})) \qquad (7)$$

Algorithm 1 summarizes the FFT operation-based data smoothing method by pseudo-code. Figure 3 shows an example of a raw signal and the corresponding smoothed signal on the Z-axis. This figure clarifies that the smoothed signal is less fluctuant than the raw signal. Therefore, we use the smoothed signal to detect the walking step.

Then you use the Lagrange multiplier y which was obtained from some other expression and then you plot it back.



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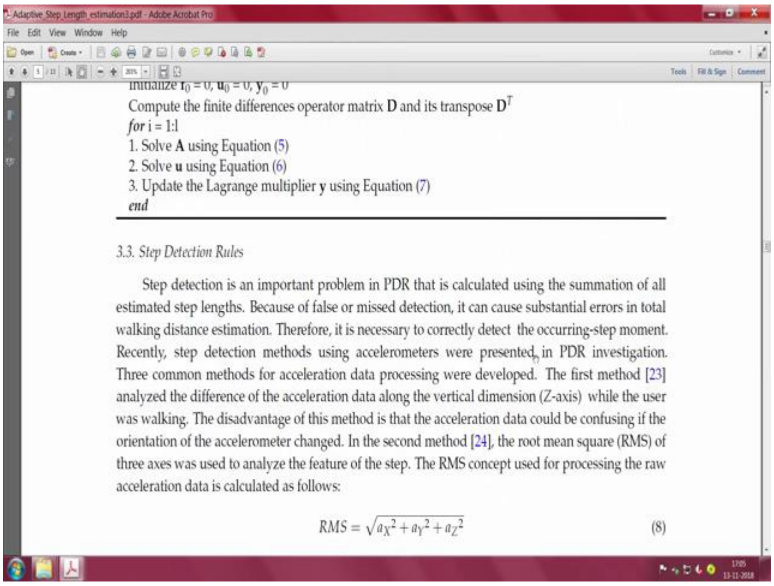
Algorithm 1 Pseudo code for FFT operation-based data smoothing method

Input data: a
Input parameter: μ
Set parameter: $\rho = 10, l = 100$
Initialize $\mathbf{f}_0 = 0, \mathbf{u}_0 = 0, \mathbf{y}_0 = 0$
Compute the finite differences operator matrix **D** and its transpose $\mathbf{D}^T$

You get back this nice smoothened signal of the z axis which is nothing, but the y which is nothing but the vertical displacement which is nothing but the yaw essentially of the phone.

Then there is a nice Pseudo code which is talking about how you do the Smoothening of the signals.

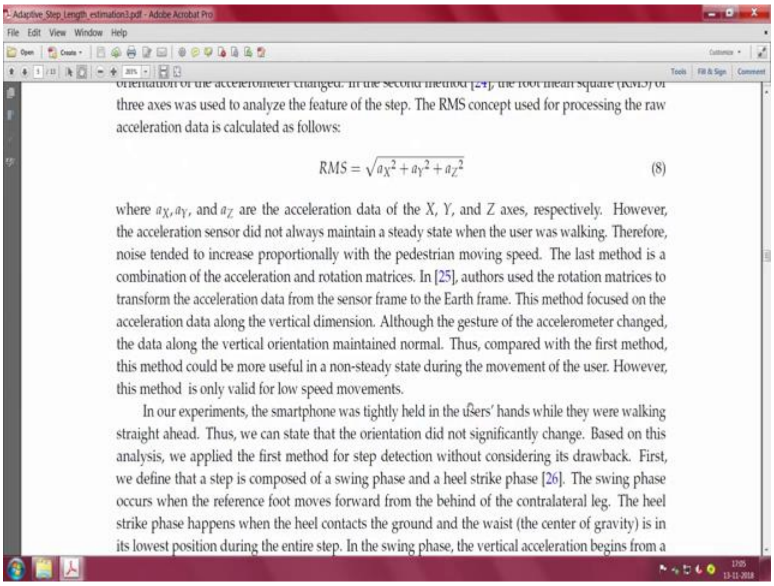


Compute the finite differences operator matrix **D** and its transpose $\mathbf{D}^T$
for i = 1:l
1. Solve **A** using Equation (5)
2. Solve **u** using Equation (6)
3. Update the Lagrange multiplier **y** using Equation (7)
end

3.3. Step Detection Rules

Step detection is an important problem in PDR that is calculated using the summation of all estimated step lengths. Because of false or missed detection, it can cause substantial errors in total walking distance estimation. Therefore, it is necessary to correctly detect the occurring-step moment. Recently, step detection methods using accelerometers were presented in PDR investigation. Three common methods for acceleration data processing were developed. The first method [23] analyzed the difference of the acceleration data along the vertical dimension (Z-axis) while the user was walking. The disadvantage of this method is that the acceleration data could be confusing if the orientation of the accelerometer changed. In the second method [24], the root mean square (RMS) of three axes was used to analyze the feature of the step. The RMS concept used for processing the raw acceleration data is calculated as follows:

$$RMS = \sqrt{a_X^2 + a_Y^2 + a_Z^2} \quad (8)$$



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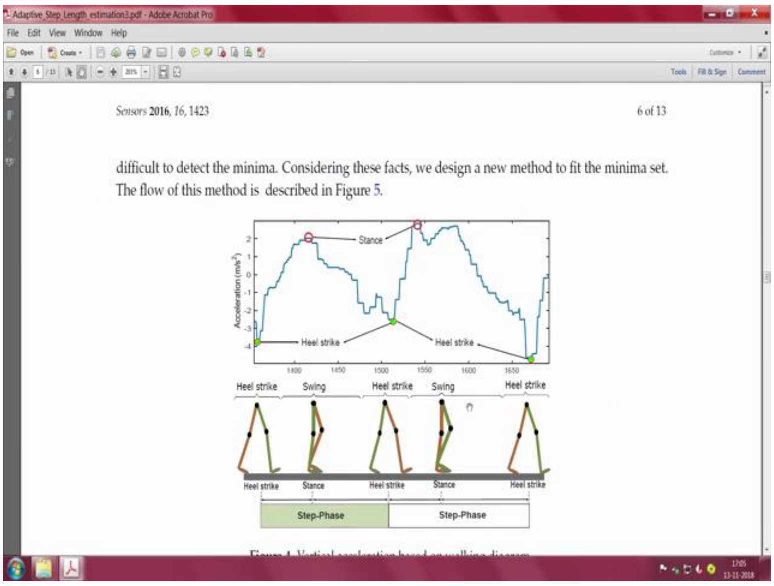
$$RMS = \sqrt{a_X{}^2 + a_Y{}^2 + a_Z{}^2} \qquad (8)$$

where a_X, a_Y, and a_Z are the acceleration data of the X, Y, and Z axes, respectively. However, the acceleration sensor did not always maintain a steady state when the user was walking. Therefore, noise tended to increase proportionally with the pedestrian moving speed. The last method is a combination of the acceleration and rotation matrices. In [25], authors used the rotation matrices to transform the acceleration data from the sensor frame to the Earth frame. This method focused on the acceleration data along the vertical dimension. Although the gesture of the accelerometer changed, the data along the vertical orientation maintained normal. Thus, compared with the first method, this method could be more useful in a non-steady state during the movement of the user. However, this method is only valid for low speed movements.

In our experiments, the smartphone was tightly held in the users' hands while they were walking straight ahead. Thus, we can state that the orientation did not significantly change. Based on this analysis, we applied the first method for step detection without considering its drawback. First, we define that a step is composed of a swing phase and a heel strike phase [26]. The swing phase occurs when the reference foot moves forward from the behind of the contralateral leg. The heel strike phase happens when the heel contacts the ground and the waist (the center of gravity) is in its lowest position during the entire step. In the swing phase, the vertical acceleration begins from a

And then step detection rules you have to do. Some RMS concept for processing raw acceleration data you use this expression and then you go on and try to improve on it.



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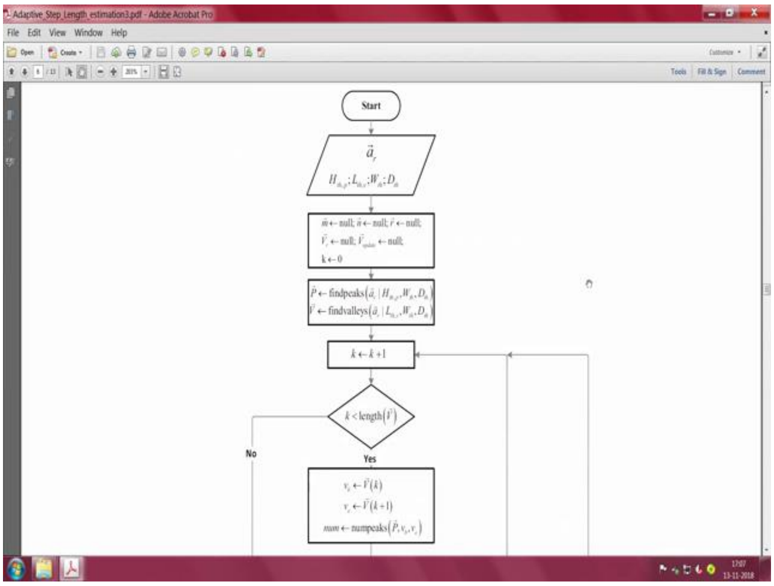
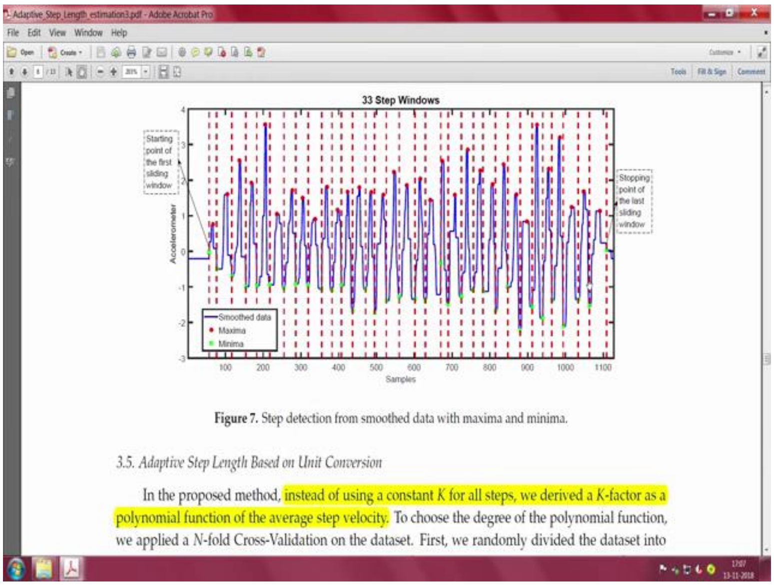
difficult to detect the minima. Considering these facts, we design a new method to fit the minima set. The flow of this method is described in Figure 5.

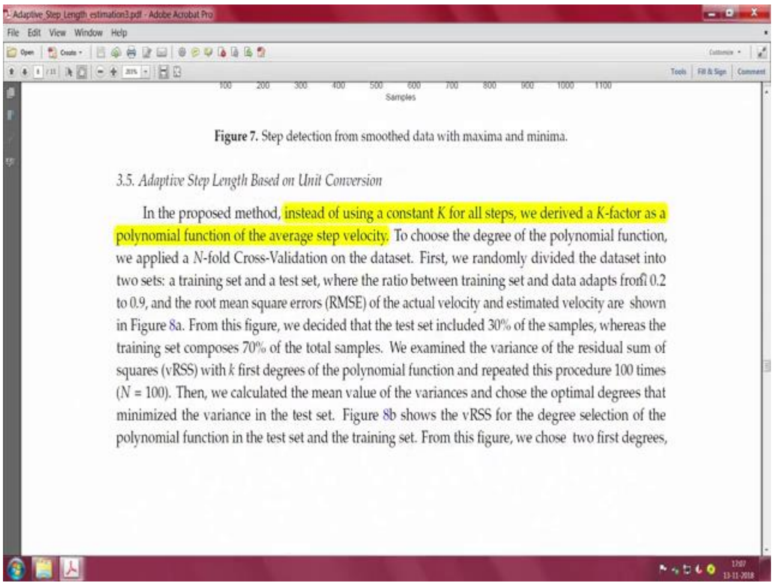
This is perhaps one paper which actually talks very well and this picture if you see this picture is exactly what we were able to plot also, you will see that there is a heel strike, then there is stance, heel strike, stance, heel strike and stance and so on. That is this hip is moving up down, up down, up down, which is what we saw in terms of that hip movement was also called the bounce in the other paper, which is nicely matching everything x axis is time and y axis is acceleration given in meter per second square the results that you see are essentially that.

Whenever there is a heel strike you will see that it is the minimum right and whenever you go to stance it goes to the maximum, why, because your leg which is like a lever sort of becomes straight and then moves the hip up moment that happens you get a stance. So, these peaks are essentially stance and the heel strikes essentially are essentially the minimum point. So, essentially it is just that part which is used.



And then you have a nice algorithm vertical acceleration based on walking distance and all. So, this paper goes on talking about their own method of trying to come up with how to estimate the Stride length.





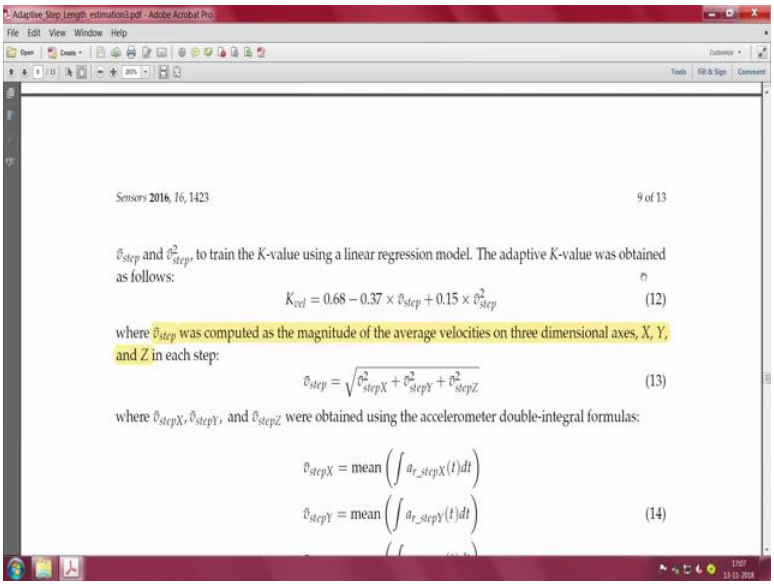
Adaptive Step Length estimation3.pdf - Adobe Acrobat Pro

Figure 7. Step detection from smoothed data with maxima and minima.

3.5. *Adaptive Step Length Based on Unit Conversion*

In the proposed method, instead of using a constant K for all steps, we derived a K-factor as a polynomial function of the average step velocity. To choose the degree of the polynomial function, we applied a N-fold Cross-Validation on the dataset. First, we randomly divided the dataset into two sets: a training set and a test set, where the ratio between training set and data adapts from 0.2 to 0.9, and the root mean square errors (RMSE) of the actual velocity and estimated velocity are shown in Figure 8a. From this figure, we decided that the test set included 30% of the samples, whereas the training set composes 70% of the total samples. We examined the variance of the residual sum of squares (vRSS) with k first degrees of the polynomial function and repeated this procedure 100 times (N = 100). Then, we calculated the mean value of the variances and chose the optimal degrees that minimized the variance in the test set. Figure 8b shows the vRSS for the degree selection of the polynomial function in the test set and the training set. From this figure, we chose two first degrees,

So, the adaptive stride length method what they do is, you have seen that value K in that expression Weinberg expression. So, instead of using the constant K for all steps we derive so, they derived a K factor as a polynomial function of the average step velocity and that is what this whole paper is all about.



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$\bar{v}_{step}$ and $\bar{v}^2_{step}$, to train the K-value using a linear regression model. The adaptive K-value was obtained as follows:

$$K_{vel} = 0.68 - 0.37 \times \bar{v}_{step} + 0.15 \times \bar{v}^2_{step} \quad (12)$$

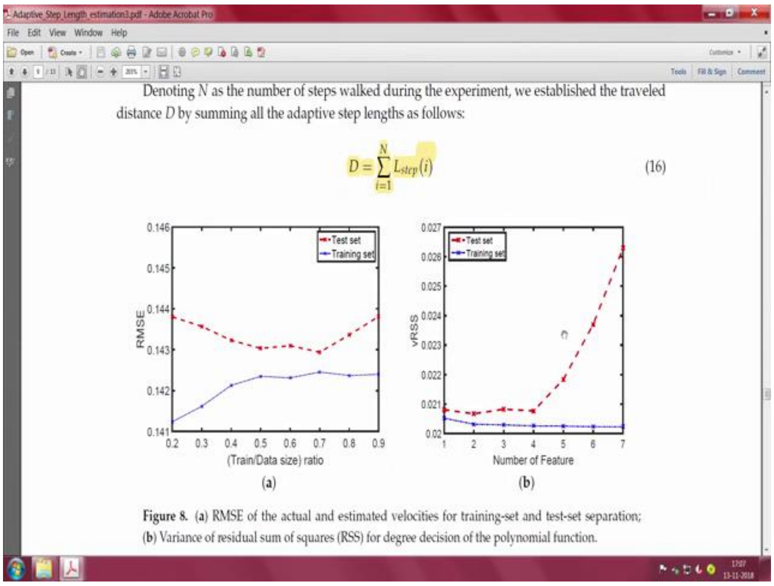
where $\bar{v}_{step}$ was computed as the magnitude of the average velocities on three dimensional axes, X, Y, and Z in each step:

$$\bar{v}_{step} = \sqrt{\bar{v}^2_{stepX} + \bar{v}^2_{stepY} + \bar{v}^2_{stepZ}} \quad (13)$$

where $\bar{v}_{stepX}$, $\bar{v}_{stepY}$, and $\bar{v}_{stepZ}$ were obtained using the accelerometer double-integral formulas:

$$\bar{v}_{stepX} = \text{mean}\left(\int a_{r\_stepX}(t)dt\right)$$
$$\bar{v}_{stepY} = \text{mean}\left(\int a_{r\_stepY}(t)dt\right) \quad (14)$$

And so, essentially you have to look for a polynomial function of the average step velocity and then they do that and then they obtain some.

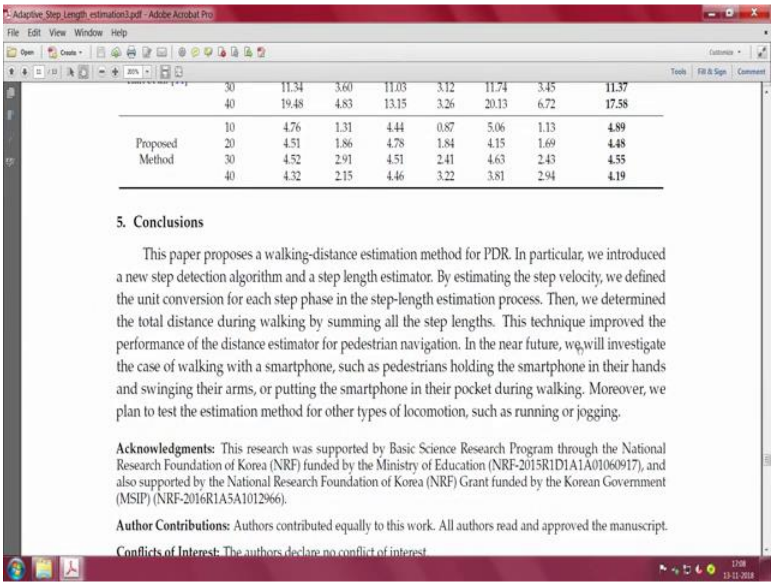


Denoting N as the number of steps walked during the experiment, we established the traveled distance D by summing all the adaptive step lengths as follows:

$$D = \sum_{i=1}^{N} L_{step}(i) \quad (16)$$

Figure 8. (a) RMSE of the actual and estimated velocities for training-set and test-set separation; (b) Variance of residual sum of squares (RSS) for degree decision of the polynomial function.

So, they collect lot of data they use some part of it for training and some part of it for testing and testing data and then they have their experimental results which and then they describe their experimental results.



	30	11.34	3.60	11.03	3.12	11.74	3.45	**11.37**
	40	19.48	4.83	13.15	3.26	20.13	6.72	**17.58**
Proposed Method	10	4.76	1.31	4.44	0.87	5.06	1.13	**4.89**
	20	4.51	1.86	4.78	1.84	4.15	1.69	**4.48**
	30	4.52	2.91	4.51	2.41	4.63	2.43	**4.55**
	40	4.32	2.15	4.46	3.22	3.81	2.94	**4.19**

5. Conclusions

This paper proposes a walking-distance estimation method for PDR. In particular, we introduced a new step detection algorithm and a step length estimator. By estimating the step velocity, we defined the unit conversion for each step phase in the step-length estimation process. Then, we determined the total distance during walking by summing all the step lengths. This technique improved the performance of the distance estimator for pedestrian navigation. In the near future, we will investigate the case of walking with a smartphone, such as pedestrians holding the smartphone in their hands and swinging their arms, or putting the smartphone in their pocket during walking. Moreover, we plan to test the estimation method for other types of locomotion, such as running or jogging.

Acknowledgments: This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2015R1D1A1A01060917), and also supported by the National Research Foundation of Korea (NRF) Grant funded by the Korean Government (MSIP) (NRF-2016R1A5A1012966).

Author Contributions: Authors contributed equally to this work. All authors read and approved the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

And finally, they do show that there is some sort of improvement with the adaptive method, they have a way to go with an adaptive K using this walking distance estimation method and in particular they introduce this new step detection algorithm and step length estimator and they have some results of that.

You can go through this paper in detail and understand them and perhaps arrive at something which you may want to try yourself.