Advanced IOT Applications
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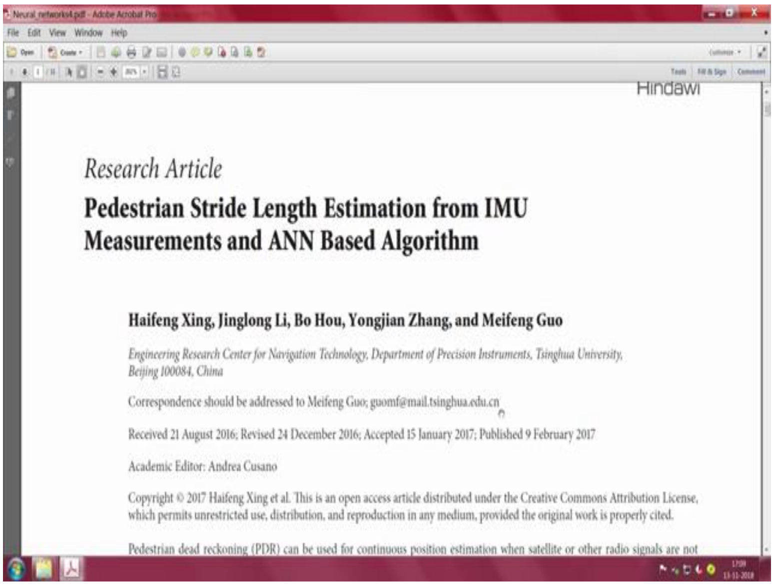
Lecture – 07
Localization using IMU Sensors – III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Research Article

Pedestrian Stride Length Estimation from IMU Measurements and ANN Based Algorithm

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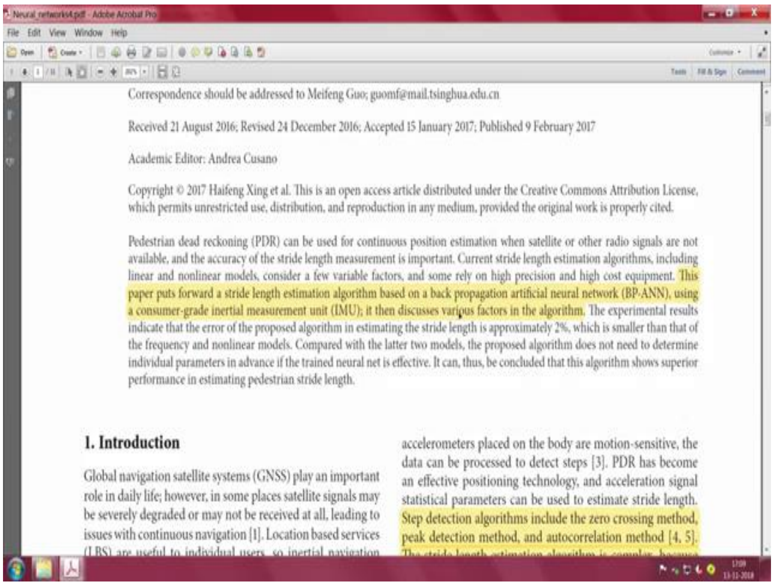
Pedestrian dead reckoning (PDR) can be used for continuous position estimation when satellite or other radio signals are not

Now let us look at the last paper in this article and this is the pedestrian stride length estimation from IMU measurements and artificial neural network based algorithm. So, you can see that very very active area of research trying to get stride length estimation.

So, I would say exciting four papers; read them thoroughly, understand them well and then you would perhaps also be at exactly the point where the needle has stopped with respect to the state of art.



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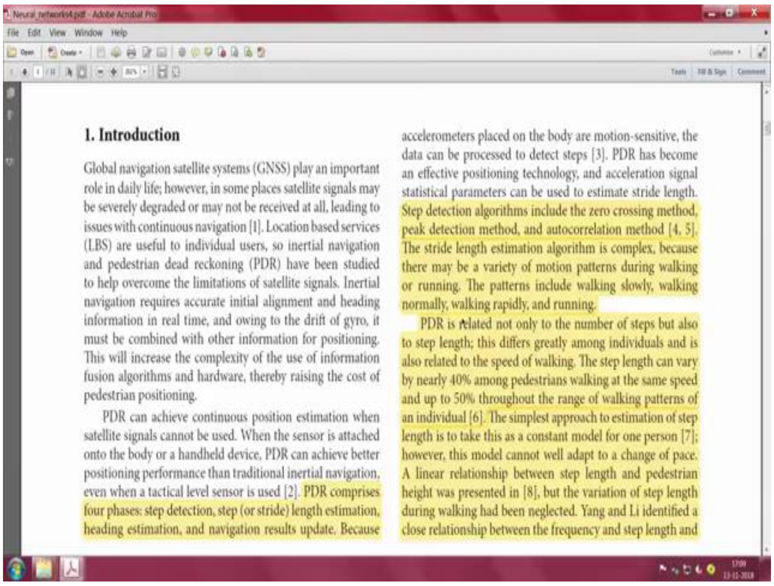
Pedestrian dead reckoning (PDR) can be used for continuous position estimation when satellite or other radio signals are not available, and the accuracy of the stride length measurement is important. Current stride length estimation algorithms, including linear and nonlinear models, consider a few variable factors, and some rely on high precision and high cost equipment. This paper puts forward a stride length estimation algorithm based on a back propagation artificial neural network (BP-ANN), using a consumer-grade inertial measurement unit (IMU); it then discusses various factors in the algorithm. The experimental results indicate that the error of the proposed algorithm in estimating the stride length is approximately 2%, which is smaller than that of the frequency and nonlinear models. Compared with the latter two models, the proposed algorithm does not need to determine individual parameters in advance if the trained neural net is effective. It can, thus, be concluded that this algorithm shows superior performance in estimating pedestrian stride length.

1. Introduction

Global navigation satellite systems (GNSS) play an important role in daily life; however, in some places satellite signals may be severely degraded or may not be received at all, leading to issues with continuous navigation [1]. Location based services

accelerometers placed on the body are motion-sensitive, the data can be processed to detect steps [3]. PDR has become an effective positioning technology, and acceleration signal statistical parameters can be used to estimate stride length. Step detection algorithms include the zero crossing method, peak detection method, and autocorrelation method [4, 5].

So, what do these papers do? This paper says, it puts forward a stride length estimation algorithm based on back propagation artificial neural network based system using a consumer grade initial measurement unit; that is the same one that most phones have.



1. Introduction

Global navigation satellite systems (GNSS) play an important role in daily life; however, in some places satellite signals may be severely degraded or may not be received at all, leading to issues with continuous navigation [1]. Location based services (LBS) are useful to individual users, so inertial navigation and pedestrian dead reckoning (PDR) have been studied to help overcome the limitations of satellite signals. Inertial navigation requires accurate initial alignment and heading information in real time, and owing to the drift of gyro, it must be combined with other information for positioning. This will increase the complexity of the use of information fusion algorithms and hardware, thereby raising the cost of pedestrian positioning.

PDR can achieve continuous position estimation when satellite signals cannot be used. When the sensor is attached onto the body or a handheld device, PDR can achieve better positioning performance than traditional inertial navigation, even when a tactical level sensor is used [2]. PDR comprises four phases: step detection, step (or stride) length estimation, heading estimation, and navigation results update. Because accelerometers placed on the body are motion-sensitive, the data can be processed to detect steps [3]. PDR has become an effective positioning technology, and acceleration signal statistical parameters can be used to estimate stride length. Step detection algorithms include the zero crossing method, peak detection method, and autocorrelation method [4, 5]. The stride length estimation algorithm is complex, because there may be a variety of motion patterns during walking or running. The patterns include walking slowly, walking normally, walking rapidly, and running.

PDR is related not only to the number of steps but also to step length; this differs greatly among individuals and is also related to the speed of walking. The step length can vary by nearly 40% among pedestrians walking at the same speed and up to 50% throughout the range of walking patterns of an individual [6]. The simplest approach to estimation of step length is to take this as a constant model for one person [7]; however, this model cannot well adapt to a change of pace. A linear relationship between step length and pedestrian height was presented in [8], but the variation of step length during walking had been neglected. Yang and Li identified a close relationship between the frequency and step length and

So, any time you talk about pedestrian dead reckoning there are four phases; they look at step detection, step or stride length estimation, heading estimation and navigation results update.

So these are the four basic steps in any of your application that you are looking at in localization without GPS topic; you may have to do these four steps when you work with IMUs.

Step detection algorithms include zero crossing method, peak detection method and autocorrelation method. Stride length estimation is complex because there are variety of motion patterns during walking or running, patterns including walking; walking slowly, walking normally, walking rapidly, running, texting mode, walking mode and all that which we already spoke about.

Now, this is also important; why your Weinberg expression is not so good this is actually telling you why. And I discussed this already once with you; PDR is related not only to the number of steps, but also the step length. This differs greatly among individuals and is related to the walking speed; we mentioned this already. Step length can vary nearly 40 percent among pedestrians walking; at the same speed and up to 50 percent throughout the range of walking patterns of an individual; within the individual itself there can be a variation and 40 percent among pedestrians walking at the same speed this is important.

So, getting to a very accurate K is known simple way; there is no simple way of getting to K which is like a constant which indeed is the struggle. People have spoken about the simplest approach of step length; take a constant model for one person, but that would not work because the model cannot adapt well; whenever there is a change in pace. Linear relationship between step length and pedestrian height some people tried that, but the variation of step length during walking has something that was not considered.

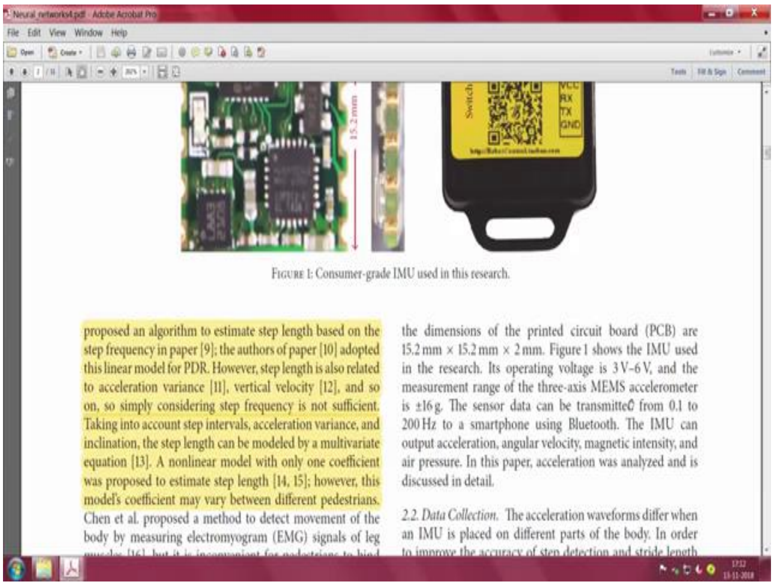


FIGURE 1: Consumer-grade IMU used in this research.

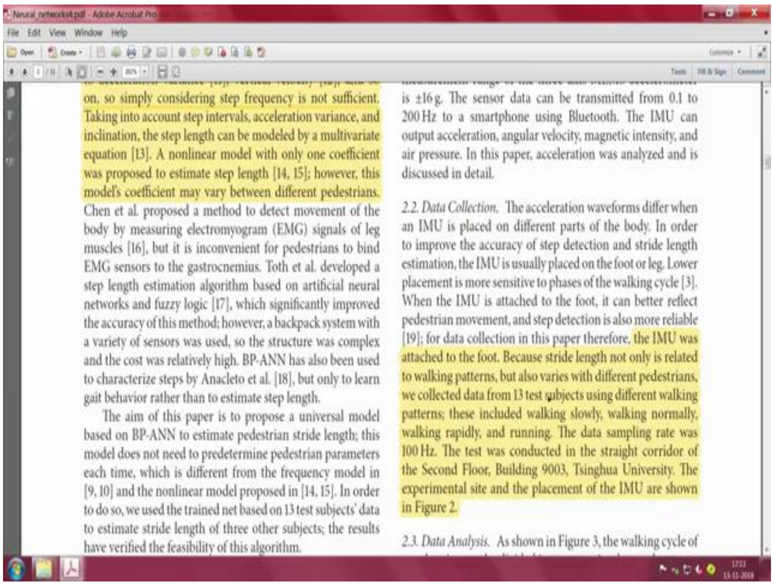
proposed an algorithm to estimate step length based on the step frequency in paper [9]; the authors of paper [10] adopted this linear model for PDR. However, step length is also related to acceleration variance [11], vertical velocity [12], and so on, so simply considering step frequency is not sufficient. Taking into account step intervals, acceleration variance, and inclination, the step length can be modeled by a multivariate equation [13]. A nonlinear model with only one coefficient was proposed to estimate step length [14, 15]; however, this model's coefficient may vary between different pedestrians. Chen et al. proposed a method to detect movement of the body by measuring electromyogram (EMG) signals of leg

the dimensions of the printed circuit board (PCB) are 15.2 mm × 15.2 mm × 2 mm. Figure 1 shows the IMU used in the research. Its operating voltage is 3 V–6 V, and the measurement range of the three-axis MEMS accelerometer is ±16 g. The sensor data can be transmitted from 0.1 to 200 Hz to a smartphone using Bluetooth. The IMU can output acceleration, angular velocity, magnetic intensity, and air pressure. In this paper, acceleration was analyzed and is discussed in detail.

2.2. Data Collection. The acceleration waveforms differ when an IMU is placed on different parts of the body. In order

Yang and Li another set of authors identified closed relationship between frequency and step length and proposed an algorithm to estimate the step length based on step frequency in some other work. The authors of paper then adapted this linear model for PDR. So, a whole bunch of work on how to get to the step length are all referenced in this.

look at the sentence, taking into account step intervals acceleration variance and inclination. The step length can be modeled by multivariate equation; a non-linear model with only one coefficient was proposed to estimate step length; however, this models coefficient may vary between different pedestrians. So, this is indeed the crux of the problem.



on, so simply considering step frequency is not sufficient. Taking into account step intervals, acceleration variance, and inclination, the step length can be modeled by a multivariate equation [13]. A nonlinear model with only one coefficient was proposed to estimate step length [14, 15]; however, this model's coefficient may vary between different pedestrians. Chen et al. proposed a method to detect movement of the body by measuring electromyogram (EMG) signals of leg muscles [16], but it is inconvenient for pedestrians to bind EMG sensors to the gastrocnemius. Toth et al. developed a step length estimation algorithm based on artificial neural networks and fuzzy logic [17], which significantly improved the accuracy of this method; however, a backpack system with a variety of sensors was used, so the structure was complex and the cost was relatively high. BP-ANN has also been used to characterize steps by Anacleto et al. [18], but only to learn gait behavior rather than to estimate step length.

The aim of this paper is to propose a universal model based on BP-ANN to estimate pedestrian stride length; this model does not need to predetermine pedestrian parameters each time, which is different from the frequency model in [9, 10] and the nonlinear model proposed in [14, 15]. In order to do so, we used the trained net based on 13 test subjects' data to estimate stride length of three other subjects; the results have verified the feasibility of this algorithm.

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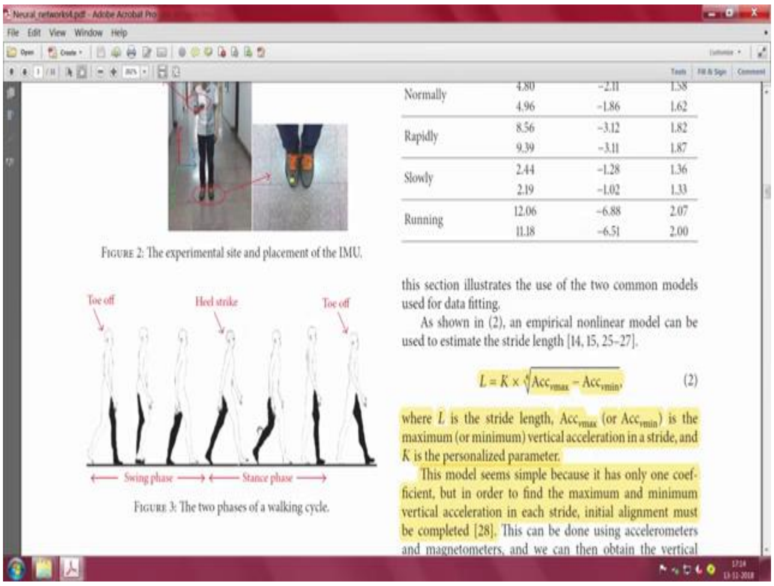
2.2. Data Collection. The acceleration waveforms differ when an IMU is placed on different parts of the body. In order to improve the accuracy of step detection and stride length estimation, the IMU is usually placed on the foot or leg. Lower placement is more sensitive to phases of the walking cycle [3]. When the IMU is attached to the foot, it can better reflect pedestrian movement, and step detection is also more reliable [19]; for data collection in this paper therefore, the IMU was attached to the foot. Because stride length not only is related to walking patterns, but also varies with different pedestrians, we collected data from 13 test subjects using different walking patterns; these included walking slowly, walking normally, walking rapidly, and running. The data sampling rate was 100 Hz. The test was conducted in the straight corridor of the Second Floor, Building 9003, Tsinghua University. The experimental site and the placement of the IMU are shown in Figure 2.

2.3. Data Analysis. As shown in Figure 3, the walking cycle of

So, really one cannot go with all the existing methods at least that is what this paper seem to claim.

And this paper also talks about how to collect data because they have to get humongous amount of data before they actually conclude on anything about estimating stride length accurately. So, they also I suppose connect the IMU on the foot because of its ability to give good signatures. And but their data is collected from just 13 test subjects that is the problem; it is still very weak because 13 is no number; it should be perhaps 130000 to arrive at very good conclusion; particularly if you are doing any neural network based systems where you do it iteratively. So, so this is really the issue.



Normally	4.80	−2.11	1.58
	4.96	−1.86	1.62
Rapidly	8.56	−3.12	1.82
	9.39	−3.11	1.87
Slowly	2.44	−1.28	1.36
	2.19	−1.02	1.33
Running	12.06	−6.88	2.07
	11.18	−6.51	2.00

Figure 2: The experimental site and placement of the IMU.

Figure 3: The two phases of a walking cycle.

this section illustrates the use of the two common models used for data fitting.

As shown in (2), an empirical nonlinear model can be used to estimate the stride length [14, 15, 25–27].

$$L = K \times \sqrt[4]{Acc_{vmax} - Acc_{vmin}}, \quad (2)$$

where L is the stride length, Acc_{vmax} (or Acc_{vmin}) is the maximum (or minimum) vertical acceleration in a stride, and K is the personalized parameter.

This model seems simple because it has only one coefficient, but in order to find the maximum and minimum vertical acceleration in each stride, initial alignment must be completed [28]. This can be done using accelerometers and magnetometers, and we can then obtain the vertical

So, you can see that the toe is off; then you have heel strike your toe is off, you have basically the same thing of heel strike and stands.

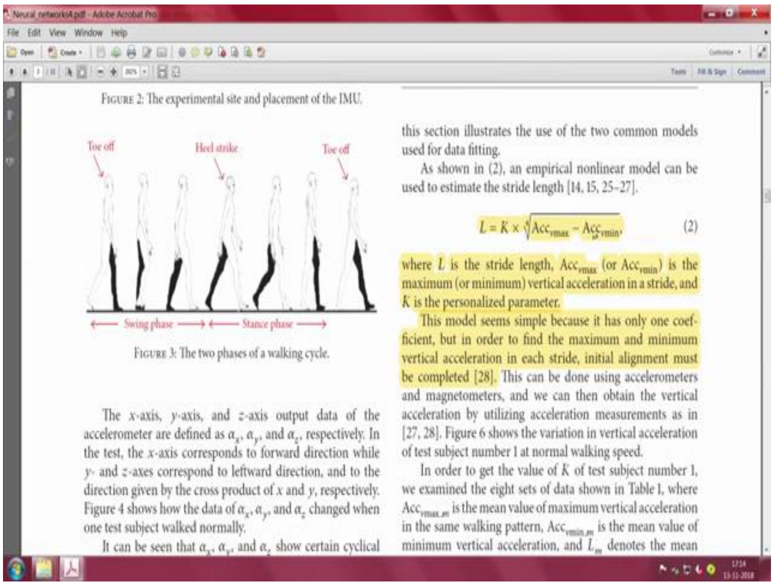


Figure 2: The experimental site and placement of the IMU.

Figure 3: The two phases of a walking cycle.

The x-axis, y-axis, and z-axis output data of the accelerometer are defined as α_x, α_y, and α_z, respectively. In the test, the x-axis corresponds to forward direction while y- and z-axes correspond to leftward direction, and to the direction given by the cross product of x and y, respectively. Figure 4 shows how the data of α_x, α_y, and α_z changed when one test subject walked normally.

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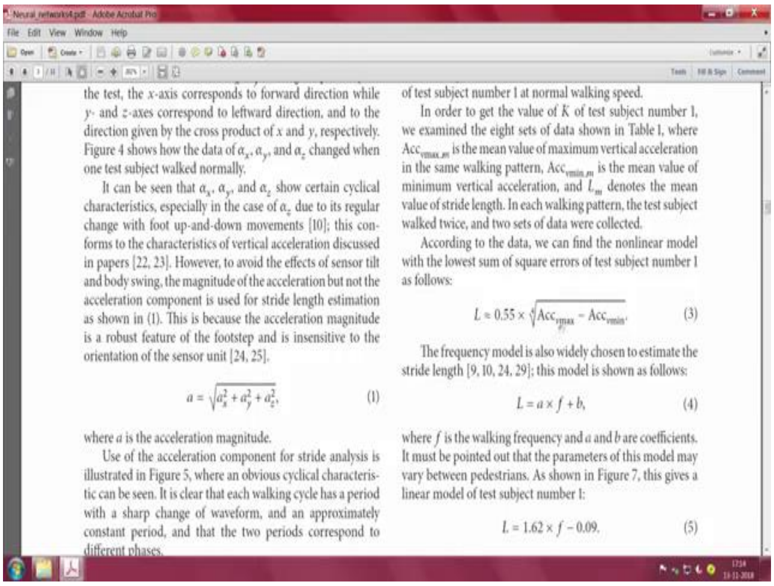
This model seems simple because it has only one coefficient, but in order to find the maximum and minimum vertical acceleration in each stride, initial alignment must be completed [28]. This can be done using accelerometers and magnetometers, and we can then obtain the vertical acceleration by utilizing acceleration measurements as in [27, 28]. Figure 6 shows the variation in vertical acceleration of test subject number 1 at normal walking speed.

In order to get the value of K of test subject number 1, we examined the eight sets of data shown in Table 1, where Acc_{vmax_m} is the mean value of maximum vertical acceleration in the same walking pattern, Acc_{vmin_m} is the mean value of minimum vertical acceleration, and L_m denotes the mean

Heel strike and stance these are the two things that they seem to be doing. And again you are back to the same expression which is an empirical non-linear model which is used for estimating the stride length. This is the famous Weinberg expression again back here. Of course, there is no n here which is this is for a single step I suppose because there is no n or n is equal to 1 you can say. This model seems simple because it is only one coefficient and but in order to find the maximum and minimum vertical axis need stride; initial alignment must be completed and that is where the whole difficulty is.



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It can be seen that α_x, α_y, and α_z show certain cyclical characteristics, especially in the case of α_z due to its regular change with foot up-and-down movements [10]; this conforms to the characteristics of vertical acceleration discussed in papers [22, 23]. However, to avoid the effects of sensor tilt and body swing, the magnitude of the acceleration but not the acceleration component is used for stride length estimation as shown in (1). This is because the acceleration magnitude is a robust feature of the footstep and is insensitive to the orientation of the sensor unit [24, 25].

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2}, \quad (1)$$

where a is the acceleration magnitude.

Use of the acceleration component for stride analysis is illustrated in Figure 5, where an obvious cyclical characteristic can be seen. It is clear that each walking cycle has a period with a sharp change of waveform, and an approximately constant period, and that the two periods correspond to different phases.

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According to the data, we can find the nonlinear model with the lowest sum of square errors of test subject number 1 as follows:

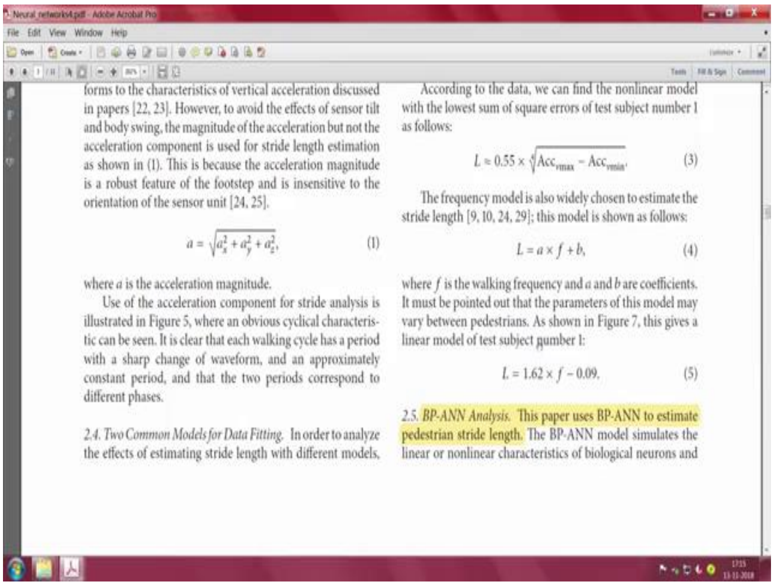
$$L \approx 0.55 \times \sqrt[4]{Acc_{vmax} - Acc_{vmin}}. \quad (3)$$

The frequency model is also widely chosen to estimate the stride length [9, 10, 24, 29]; this model is shown as follows:

$$L = a \times f + b, \quad (4)$$

where f is the walking frequency and a and b are coefficients. It must be pointed out that the parameters of this model may vary between pedestrians. As shown in Figure 7, this gives a linear model of test subject number 1:

$$L = 1.62 \times f - 0.09. \quad (5)$$



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2.4. Two Common Models for Data Fitting. In order to analyze the effects of estimating stride length with different models,

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2.5. BP-ANN Analysis. This paper uses BP-ANN to estimate pedestrian stride length. The BP-ANN model simulates the linear or nonlinear characteristics of biological neurons and

This paper goes on to substitute K as 0.55 and tries to come up with some expression, but miserably says that it is not the right way to do because this is not going to work for several people. Then they propose this back propagation artificial neural network analysis to estimate the pedestrian stride length.

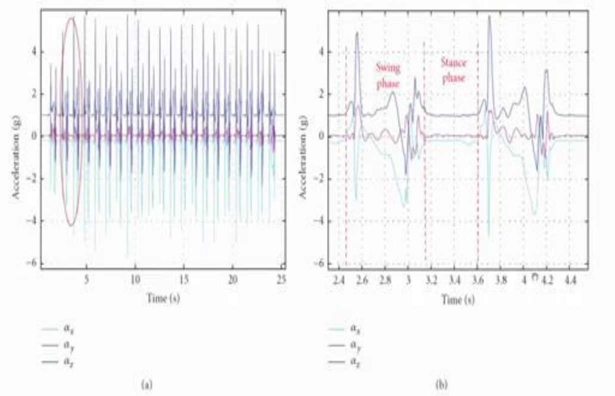

Figure 4: (a) The variation of a_x, a_y, and a_z. (b) A partially enlarged view of the portion circled by the red ellipse.

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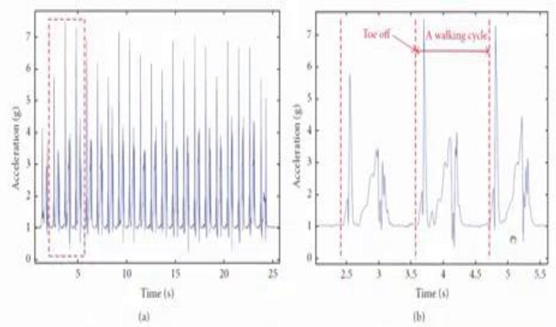

Figure 5: (a) The variation in the acceleration of one test subject walking normally. (b) Magnification of the section delineated by a red rectangle.

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is a powerful study system. It can achieve nonlinear mapping between inputs and outputs. It consists of an input layer, hidden layer, and output layer, and its classical architecture is shown in Figure 8. Its weights and thresholds are continuously adjusted, to approximate the desired input and output mapping relationship.

The active function of the hidden layer is the sigmoid function presented in (6), while the output layer is a linear function

$$g(x) = \frac{1}{1+e^{-x}}, \quad (6)$$

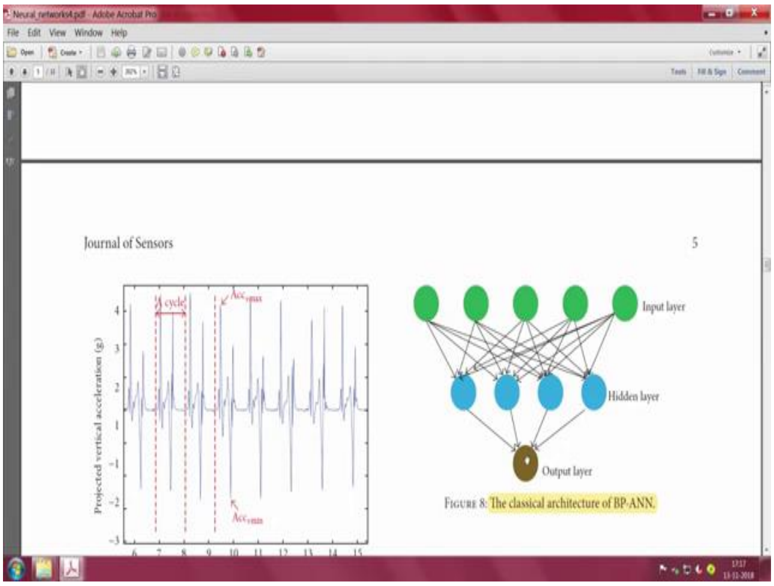
where x is the independent variable.

The input of neurons in the hidden layer can be described as

$$v_i = \sum_{j=1}^{n_0} w_{ij}x_j + b_i, \quad (7)$$

where v_i is the input of the ith neuron in the hidden layer, w_{ij} is the connection weight of the ith neuron of the input layer to the jth neuron of the hidden layer, and x_j denotes the input of the jth neuron of the input layer. n_0 is the number of neurons in the input layer, and b_i is the threshold of the ith neuron of the hidden layer.

So, what do they do here? As you know any artificial neural network will have basically three layers; an input layer you will have a hidden layer and you will have an output layer.



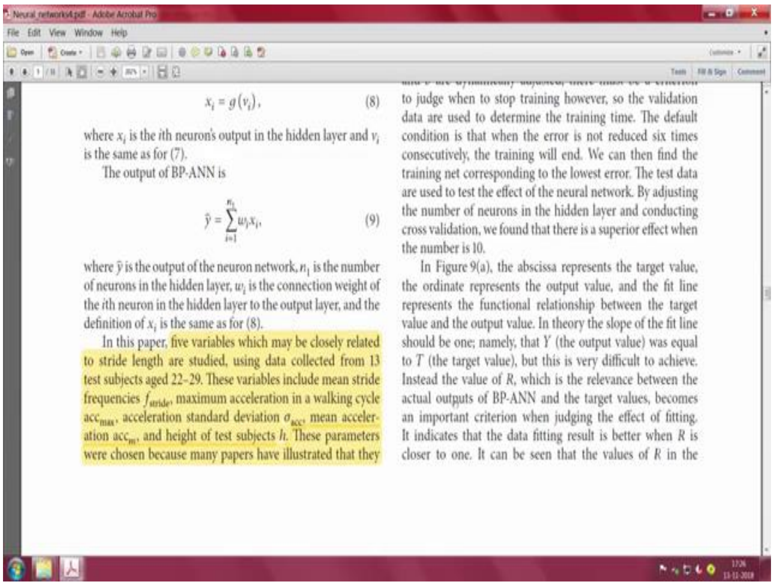
The inputs layer will only have the inputs to be fed, which is passed to the hidden layer where some kind of nonlinear mapping is done. Further the hidden layer output is passed to the output layer where suitable function gives us a desired result.

So, the output that you actually see will be in this expression nothing, but the y hat or the y cap which you will see out here. And then you will find an expression; you will find a function here essentially these are all non-linear functions and we will look at these functions one by one.

So, let us see this, essentially you have inputs which are to be fed to the input layer, we will have to understand what are the inputs. And then what is the activation function here in the hidden layer? And then we have to also know what is the output layer activation function. So, you need activation function for the hidden and output layers.

So, let us go and see what these activation functions are all about and what it can achieve, so what does a neural network do? It can achieve non-linear mapping between inputs and outputs. It consists of input; hidden and output layers and its weights and thresholds are continuously adjusted to approximate the desired input and output mapping relationship.

Now, the active function of the hidden layer is a sigmoid function; you could refer this reference 6. And in fact, there are several such functions; one of the functions is indeed the sigmoid function that they choose; while the output layer is a linear function. So, this is a sigmoid function; the active function of the hidden layer is the sigmoid function, while the output layer is a linear function.



$$x_i = g(v_i), \quad (8)$$

where x_i is the ith neuron's output in the hidden layer and v_i is the same as for (7).

The output of BP-ANN is

$$\hat{y} = \sum_{i=1}^{n_1} w_i x_i, \quad (9)$$

where $\hat{y}$ is the output of the neuron network, n_1 is the number of neurons in the hidden layer, w_i is the connection weight of the ith neuron in the hidden layer to the output layer, and the definition of x_i is the same as for (8).

In this paper, five variables which may be closely related to stride length are studied, using data collected from 13 test subjects aged 22–29. These variables include mean stride frequencies f_{stride}, maximum acceleration in a walking cycle acc_{max}, acceleration standard deviation σ_{acc}, mean acceleration acc_m, and height of test subjects h. These parameters were chosen because many papers have illustrated that they

to judge when to stop training however, so the validation data are used to determine the training time. The default condition is that when the error is not reduced six times consecutively, the training will end. We can then find the training net corresponding to the lowest error. The test data are used to test the effect of the neural network. By adjusting the number of neurons in the hidden layer and conducting cross validation, we found that there is a superior effect when the number is 10.

In Figure 9(a), the abscissa represents the target value, the ordinate represents the output value, and the fit line represents the functional relationship between the target value and the output value. In theory the slope of the fit line should be one; namely, that Y (the output value) was equal to T (the target value), but this is very difficult to achieve. Instead the value of R, which is the relevance between the actual outputs of BP-ANN and the target values, becomes an important criterion when judging the effect of fitting. It indicates that the data fitting result is better when R is closer to one. It can be seen that the values of R in the

So, let us look at them; what you feed we take five variables this is nicely marked here five variables which may be closely related to the stride length are studied; using data collected from 13 subjects aged 22 to 29.

The variables include mean stride frequencies fstride, maximum acceleration in the walking cycle acc_{max}, acceleration standard deviation sigma acc, mean acceleration acc m and height of the test subjects h. And essentially, they are trying to train, taking these as inputs; train this model recursively and then come up with some output y hat.

Now, what is y hat? y hat being the output is the output of the neural. In this because you are looking at a function output of the BP-ANN function; you have to look at the output layer.

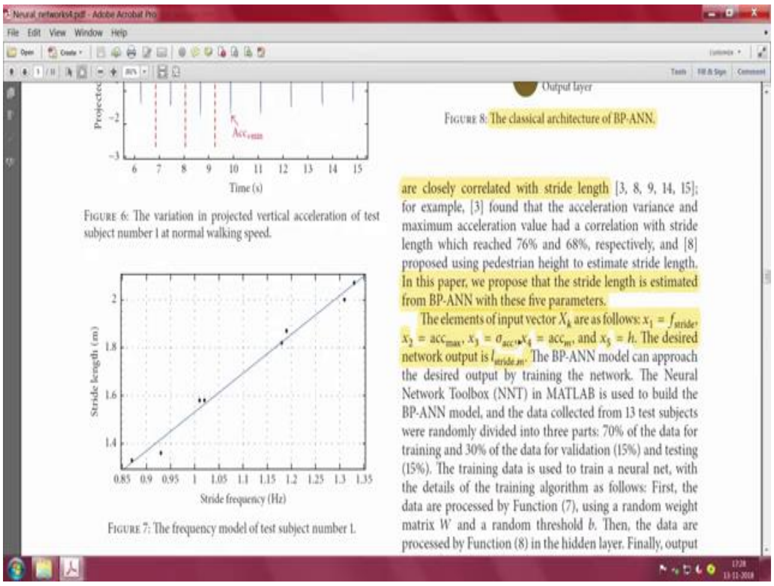


Figure 8: The classical architecture of BP-ANN.

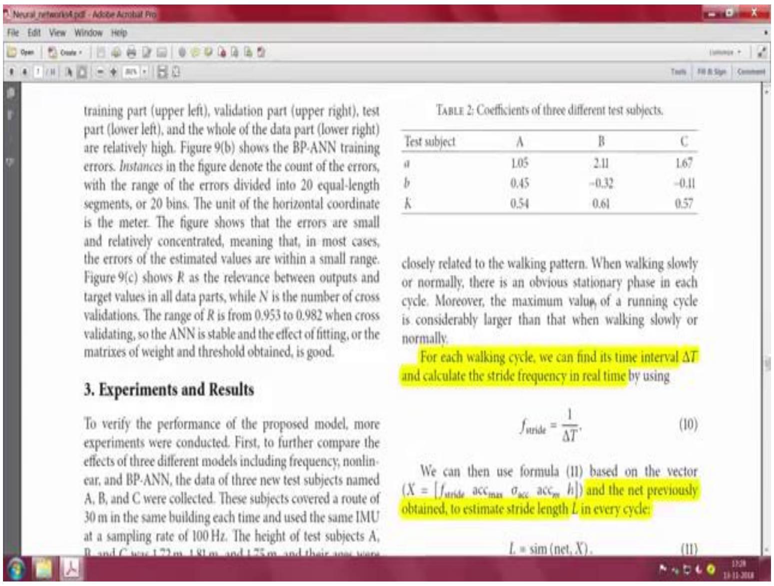
Figure 6: The variation in projected vertical acceleration of test subject number 1 at normal walking speed.

Figure 7: The frequency model of test subject number 1.

are closely correlated with stride length [3, 8, 9, 14, 15]; for example, [3] found that the acceleration variance and maximum acceleration value had a correlation with stride length which reached 76% and 68%, respectively, and [8] proposed using pedestrian height to estimate stride length. In this paper, we propose that the stride length is estimated from BP-ANN with these five parameters.

The elements of input vector X_k are as follows: $x_1 = f_{stride}$, $x_2 = acc_{max}$, $x_3 = \sigma_{acc}$, $x_4 = acc_m$, and $x_5 = h$. The desired network output is $l_{stride,m}$. The BP-ANN model can approach the desired output by training the network. The Neural Network Toolbox (NNT) in MATLAB is used to build the BP-ANN model, and the data collected from 13 test subjects were randomly divided into three parts: 70% of the data for training and 30% of the data for validation (15%) and testing (15%). The training data is used to train a neural net, with the details of the training algorithm as follows: First, the data are processed by Function (7), using a random weight matrix W and a random threshold b. Then, the data are processed by Function (8) in the hidden layer. Finally, output

Then what they do? They run this neural network and then they sort of try to correlate the stride length as accurately as possible to ground truth and they have some results appearing here.



training part (upper left), validation part (upper right), test part (lower left), and the whole of the data part (lower right) are relatively high. Figure 9(b) shows the BP-ANN training errors. *Instances* in the figure denote the count of the errors, with the range of the errors divided into 20 equal-length segments, or 20 bins. The unit of the horizontal coordinate is the meter. The figure shows that the errors are small and relatively concentrated, meaning that, in most cases, the errors of the estimated values are within a small range. Figure 9(c) shows R as the relevance between outputs and target values in all data parts, while N is the number of cross validations. The range of R is from 0.953 to 0.982 when cross validating, so the ANN is stable and the effect of fitting, or the matrixes of weight and threshold obtained, is good.

3. Experiments and Results

To verify the performance of the proposed model, more experiments were conducted. First, to further compare the effects of three different models including frequency, nonlinear, and BP-ANN, the data of three new test subjects named A, B, and C were collected. These subjects covered a route of 30 m in the same building each time and used the same IMU at a sampling rate of 100 Hz. The height of test subjects A, B and C was 1.72 m, 1.81 m, and 1.75 m, and their ages were

Table 2: Coefficients of three different test subjects.

Test subject	A	B	C
a	1.05	2.11	1.67
b	0.45	−0.32	−0.11
K	0.54	0.61	0.57

closely related to the walking pattern. When walking slowly or normally, there is an obvious stationary phase in each cycle. Moreover, the maximum value of a running cycle is considerably larger than that when walking slowly or normally.

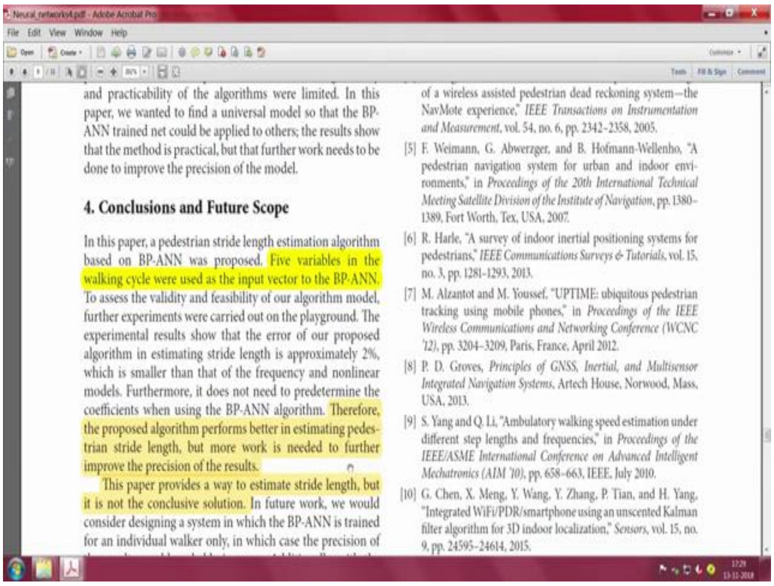
For each walking cycle, we can find its time interval ΔT and calculate the stride frequency in real time by using

$$f_{stride} = \frac{1}{\Delta T}. \quad (10)$$

We can then use formula (11) based on the vector $(X = [f_{stride}\ acc_{max}\ \sigma_{acc}\ acc_m\ h])$ and the net previously obtained, to estimate stride length L in every cycle:

$$L = \text{sim}(\text{net}, X). \quad (11)$$

So, this paper is also interesting because it applies back propagation neural network; artificial neural network. And this further says how do you calculate the inputs you need, fstride as we discussed. So, you get fstride from the time interval of each walking cycle.



and practicability of the algorithms were limited. In this paper, we wanted to find a universal model so that the BP-ANN trained net could be applied to others; the results show that the method is practical, but that further work needs to be done to improve the precision of the model.

4. Conclusions and Future Scope

In this paper, a pedestrian stride length estimation algorithm based on BP-ANN was proposed. Five variables in the walking cycle were used as the input vector to the BP-ANN. To assess the validity and feasibility of our algorithm model, further experiments were carried out on the playground. The experimental results show that the error of our proposed algorithm in estimating stride length is approximately 2%, which is smaller than that of the frequency and nonlinear models. Furthermore, it does not need to predetermine the coefficients when using the BP-ANN algorithm. Therefore, the proposed algorithm performs better in estimating pedestrian stride length, but more work is needed to further improve the precision of the results.

This paper provides a way to estimate stride length, but it is not the conclusive solution. In future work, we would consider designing a system in which the BP-ANN is trained for an individual walker only, in which case the precision of

of a wireless assisted pedestrian dead reckoning system—the NavMote experience," *IEEE Transactions on Instrumentation and Measurement*, vol. 54, no. 6, pp. 2342–2358, 2005.

[5] F. Weimann, G. Abwerzger, and B. Hofmann-Wellenho, "A pedestrian navigation system for urban and indoor environments," in *Proceedings of the 20th International Technical Meeting Satellite Division of the Institute of Navigation*, pp. 1380–1389, Fort Worth, Tex, USA, 2007.

[6] R. Harle, "A survey of indoor inertial positioning systems for pedestrians," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 3, pp. 1281–1293, 2013.

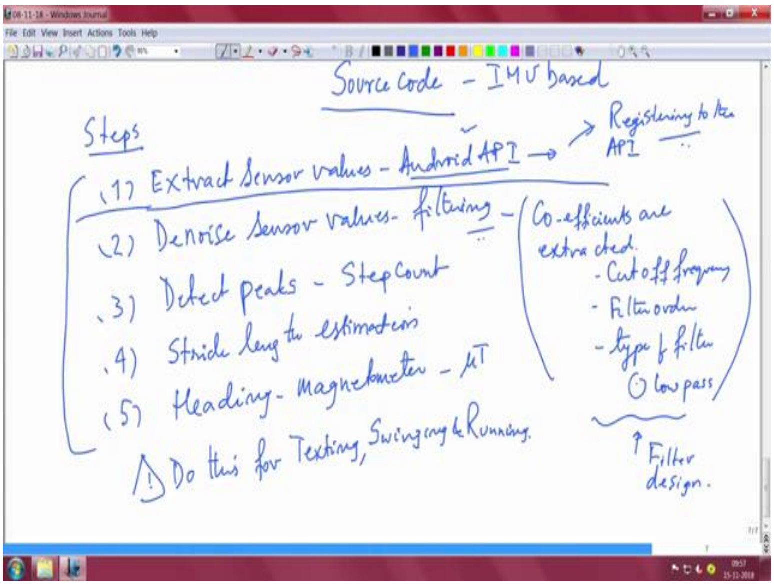
[7] M. Alzantot and M. Youssef, "UPTIME: ubiquitous pedestrian tracking using mobile phones," in *Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC '12)*, pp. 3204–3209, Paris, France, April 2012.

[8] P. D. Groves, *Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems*, Artech House, Norwood, Mass, USA, 2013.

[9] S. Yang and Q. Li, "Ambulatory walking speed estimation under different step lengths and frequencies," in *Proceedings of the IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM '10)*, pp. 658–663, IEEE, July 2010.

[10] G. Chen, X. Meng, Y. Wang, Y. Zhang, P. Tian, and H. Yang, "Integrated WiFi/PDR/smartphone using an unscented Kalman filter algorithm for 3D indoor localization," *Sensors*, vol. 15, no. 9, pp. 24595–24614, 2015.

So, essentially this is also saying that you could apply these modern techniques; in order to arrive at very accurate stride length. So, the conclusion of this work is five variables in the walking cycle were used as an input vector to the back propagation artificial neural network. And they say they claim that it is better in performing pedestrian stride length estimation.



So, there are five steps involved in building the application:

- Extract sensor values.

- Filter the sensor values in real time.
- Detect the peaks which in turn gives step detected indication.
- Get the maxima and minima value from the peaks and estimate the stride length.
- Update the distance along the heading information.

So, in a sense this is what you will have to get to put together when you try and prototype your application. Now all of this what we are just seeing now is for one mode essentially right. It could be for texting, swinging and running; You will have to see how to improve this application for other modes as well.

Also please note that we will give you a Barebone code where the core algorithm will not be mentioned. So, you will find in one place insert your code here. So, what you should insert will also be mentioned. So, at exactly that point you will have to write your own code and make a nice application for let us say texting mode.

Thank you.