IMU Acceleration Drift Compensation for Position Tracking in Ambulatory Gait Analysis

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Abstract: This study is a part of a project where we target determining discriminative features to define diseases that cause disorders in the human vestibular system. For this purpose we aim to analyze the gait of the person. Among a number of parameters used for gait analysis, some make use of the foot- and knee positions. Hence the exact determination of position is of great importance. Here we use inertial sensors (IMU) placed on foot and knee in order to calculate the displacement by double integrating the free acceleration output data of the sensor. Thus, the overall position accuracy is highly dependent on the accuracy of the acceleration data where the offset and drift play great role in its corruption. We propose a method to minimize the error due to sensor offset and drift by utilizing the fact that there are gait intervals where the foot rests. The results are promising that the calculated average error is low; though the standard deviation needs some further amendment.

1 INTRODUCTION

The vestibular system is one of the most important survival skills in human life. In connection with others the vestibular system provides the link of the individual with the physical environment. (Hansson et al., 2010). A weakness or an interruption in the operation of this system would cause disruption in spatial orientation and thus affect the connection of the person with several fields of life such as work, education, social life etc. (Gaerlan, 2010). Measuring the body posture and its stability, processing the data collected from active gait and rest are hot topics in literature about human balance. (Chang et al., 2012; Basta et al., 2013; Galna, 2014).

Table 1 lists some of the gait parameters that are examined for clinical purposes in literature (Herran et al., 2014).

Table 1: Some gait parameters observed for clinical purposes.

Stride velocity	Stride length
Step length	Cadence
Step Width	Traversed distance
Route	Long-term monitoring of gait
Step time	Stop duration

There are three main approaches for gait analysis: Image processing, using floor sensors and capture data from sensors placed on the body (Herran et al., 2014).

The methods based on image processing generally use cameras to record the gait and the captured data will be processed as to filter the image to get a black and white copy only, to count pixels (either light ones or dark) etc. which will help to analyze the gait (Pratheepan et al., 2009; Chang et al., 2009)

Another popular method for gait analysis is using floor sensors. Here usually pressure sensors are positioned along a floor where the walk takes place. The data acquired by the sensors will then be processed on a digital platform to give information about the quality of the gait (Vera-Rodriguez et al., 2013).

Another group of methods for gait analysis makes use of wearable sensors that are positioned on several parts of the body (Tao et al., 2012; Abdul Razak, 2012). Some of the popular sensors used for this purpose are: Accelerometers, gyros, piezoelectric/piezoresistive pressure sensors, goniometer sensors etc.

Each sensor has its pros and cons. For example one of the main problems with the goniometer is that

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goniometers attached on the body lose their position during the motion (Roatenberg et al., 2013). Another remarkable problem is the alignment of the angle measuring sensor with the joints. This problem increases with an increase in the number of the degree of freedom of the joint.

Around 38% of the methods used for gait analysis are based upon inertial-sensor based systems (Herran et al., 2014). An inertial sensor that houses 3D accelerometers, gyroscopes and magnetometers can provide accurate orientation data at least for short time intervals. Gyroscopes measure angular velocity where accelerometers provide the acceleration vector in sensor coordinates.

Yavuzer, G. indicates that three dimensional balance and walking analysis system is the most important diagnosis tool to assess the integrity of orthopedic and vestibular system. Camera based and static systems that are integrated to hospital environment have low mobility and high charge. Instead, wearable sensors that help inertial measurement will enhance the quality of the analysis and free the patient from being in a special environment making the outdoor data acquisition possible (Yavuzer, 2009). Alberts, J. L. et al. studied center of gravity computing and postural stability where data was collected by the gyroscope inside ipad 2 and they compared the results with Neurocom computarized dynamic posturography. The results obtained from dynamic posturography and ipad 2 were declared to be quite close. In accordance with this information, the authors put forth that gyroscope is a good means to measure center of gravity and postural stability (Alberts et al., 2015). Tadano S. et.al. studied wearable acceleration and location sensors where they focused on body posture, position and motion symmetry of body segments such as hip, knee and ankle. The authors announced that compared to systems capturing and processing motion with camera, this method gave a better qualified and real-time documentation of motion. They concluded that acquiring angular data and measuring motion speed with high precision is possible with wearable sensors (Tadano et al., 2013).

The wearable sensors are usually located on feet, ankles, knees and waist (Roatenberg et al., 2013). In our project we are also using wearable sensors. A close look to Table 1 puts forth that determination of the correct position of feet is of great importance. On the whole of the project, data collected from motion sensors placed on the body and the insole pressure sensors will be of interest; but this study focuses on some vital problems faced when acquiring data from motion sensors positioned on certain locations on the leg only. We are mainly interested in determining the correct position of the foot within a limited walk-path length (11.5m). Thus, the frame of this study is restricted with the search for the solution to offset and drift problems of the accelerometer data in inertial sensors to give correct position data.

In order to describe the way we go to reach our aim the rest of the paper is arranged as follows: In Section 2 we first define the problem with the acceleration data and we introduce the sensor used in our study. Section 2 also gives explanation about previous work and its reflection on this study. The proposed method to obtain the correct position information and considerations about the estimation of the error is handled in Section 3. This section further presents the experimental set-up and sample graphs of uncorrected and corrected data according to the introduced method. This section is followed by experimental results and error calculation. Finally we discuss conclusions drawn and give perspective about future work.

2 CORRECTION OF THE ORIENTATION/ POSITION DATA

Almost all inertial sensors suffer from integration drift. The main problem is that the position error accumulates in time to reach a remarkable value if it is not reset or compensated. Since the position information is obtained by double integrating the acceleration over time, the main source of error is the possible wrong data to give the acceleration that has its source in sensor noise, sensor signal offset and/or sensor orientation error. Drift may arise from mechanical stresses, aging, temperature changes etc. (Tuck, 2007).

As explained before in this study we are concentrated on minimizing the effect of the offset and drift of the acceleration data on position determination. In fact even the offset wouldn't be much harmful if it would not drift since cancellation of a constant DC shift is not much exhausting.

In our project we use the MTW2 Wireless 3DOF Motion Tracker from Xsens, each sensor comprised of 3D accelerometers, 3D gyroscopes and 3D magnetometers (xsens.com).

2.1 Brief Background

Inside an inertial sensor, orientation data is usually corrected by extended Kalman filters (Bennett et al., 2014; Won, 2010). Nevertheless the offset and drift of the sensor requires continuous tracking of the error for compensation during the operation. Again the favourite technique is the use of Kalman filter to estimate the next value accurately by utilizing a reliable reference. The problem is even more complicated when handling with motion tracking of human since there are a lot of body segments which have to be aligned with sensors. To ease the mathematical complexity quaternions help a lot, but still there is hard work to do to overcome the alignment and the error problems. The body dimensions need to be measured to estimate joint positions and joint measurement updates serve for correction of uncertainties sourced from sensor noise and movement-related errors (Roatenberg et al., 2013).

2.2 Calibration of Accelerometer Output

Though we are interested in the gait analysis we do not have deep concern in full human motion for the time being. We restrict our interest mainly with the position of foot. Thus the correct acceleration data of the inertial sensor is vital for us.

Various studies are focused on calibrating accelerometer output data in literature (Bennett et al., 2014; Lee, 2016). A conspicuos study investigates the correction of the acceleration data of an inertial measurement unit (IMU) via various test beds such as optical mouse, turntable and shake table (Kamer and Ikizoglu, 2013). Here the authors used the collected data from the test beds to train artificial neural networks (ANN) which would improve the accelerometer outputs by estimating the reference data from the actual sensor outputs. The resulting goodness of fit was reached as high as 72% which was significantly higher than the goodness of fit reached with classical low-pass filters giving a value around 61%.

In our study the x- and y-axes of two sensors of the set are also corrected with the optical mouse (Brand A4Tech, model X5-6AK) and a 'Back-propagation Levenberg – Marquardt method' based ANN with two hidden layers of 8 and 4 neurons respectively is trained similar to the referenced study with a size of 28 for the train set and 13 for the test set. We reached a goodness of fit as 74% for a linear displacement of 5m. Moreover the ANN results are compared with several system identification methods using Matlab System Identification Toolbox 7.2.1. The results are brought together to form Table 2.

Once having obtained these values for the goodness of fit, we wonder whether we can increase the accuracy in determining the position during the walk without using complex tools to correct the acceleration data. Here we take advantage of the fact that the human gait has its characteristic that there are durations where the foot is motionless; in other words the velocity is zero. Hence, these durations can be used to prevent the accumulation of the position error.

Though our final aim with the project is to discover significant features to point sources of several balance disorders, in this study we have limited our frame with limited gait analysis along 11.5 meters. Hence, we have got a measure to verify the accuracy of the proposed method.

3 ALGORITHM OVERVIEW

3.1 Data Acquisition Environment

All the data is collected in Cerrahpasa Medical School. Care is taken that environmental conditions do not influence the inertial data. As an example, within the sensor module free acceleration data is constructed by referencing the magneting field of earth via magnetometers. This conditions that in order to preserve the reliability no source causing magnetic field should exist nearby when collecting data. So, data is acquired on weekends when all the offices were closed. Furthermore we have used a flat path to ensure zero final change in z-axis position data at the end of the walk.

3.2 Applied Method and Error Estimation

We decided to use the free acceleration data provided by the manufacturer of the sensor system since this data is expected to be compensated well enough against certain perturbers by Kalman updates (Roatenberg et al., 2013).

The free data references the global frame, but not the sensor axes. Thus, for the same direction of movement the position of the sensor on the body doesn't care to give similar values.

In our study for each axis we calculate the mean of acceleration for 1 sec (between the instants 2sec and 3sec) when resting before starting the test and then subtract the mean from all the following instantenous acceleration values to compensate the acceleration offset. Now that the drift in acceleration

Table 2: Goodness-of-fit results obtained with system identification methods.

Model	Model Structure	Training set – Goodness of fit (%)	Test set – Goodness of fit (%)
Linear parametric models			
ARMAX	[na(2) nb(2) nc(2) nk(1)] $A(q)y(t) = B(q)u(t-nk) + C(q)e(t)$	65.80	61.75
BJ (Box-Jenkins)	[nb(4) nf(4) nc(4) nd(4) nk(1)] $y(t) = \frac{B(q)}{F(q)}u(t-nk) + \frac{C(q)}{D(q)}e(t)$	65.90	62.10
State space	[na=nb=nk=nc=nd(4)] $x(t+1) = Ax(t) + Bu(t) + Ke(t)$ $y(t) = Cx(t) + Du(t) + e(t)$	64.95	61.20
Nonlinear models			
Nonlinear ARX	[na(2) nb(2) nk(1)] $A(q)y(t) = B(q)u(t-nk) + e(t)$ Nonlinear regression $y(t-1), y(t-2), u(t-1), u(t-2)$	63.11	57.68
Hammerstein-Wiener	[nb(2) nf(3) nk(1)] $y(t) = \frac{B(q)}{F(q)}u(t-nk) + e(t)$ Nonlinear estimator - 10 piece- linear estimator	67.48	59.84
Correlation models			
	[m(20) n(10)] $A_0 y(t) = B_0 u(t) + B_1 u(t-T) + \ldots + B_m u(t-mT) + A_1 y(t-T) + \ldots + A_n y(t-nT)$	75.63	71.71

can not be compensated easily, we bring the approach that the velocity will be reset at every rest of the foot to prevent the accumulation of the position error.

Let us discuss the matter on a numerical example where the distance is 10m. This value for the path length is taken in order to adapt the considerations to the widely used clinical test techniques such as the 'Timed 25-Foot Walk (T25-FW)' technique (Herran, A.M. et al., 2014) where the time is measured that elapses to walk a straight line of 7.5m distance and the linearity of the gait during this period is analyzed. An acceleration offset drift of a_{off} = 0.05m/sec^2 causes in 10 seconds a position error of:

$$\Delta p = \frac{a_{off} t^2}{2} = \pm 2.5m$$

If the path taken within this time is 10m, the error will be 25%. Observations put forth that a full step period is around 1sec, where half of this time is the step time and the other half the rest time of the related foot. Hence, if the velocity offset is reset at every foot rest, so approximately every 0.5sec that nearly corresponds to a step time, the position error after 10m will be: Total absolute position error (Tpe) = (Number of steps) x (position error in each step length); thus giving:

$$Tpe = 10 \cdot a_{off} \cdot t^2 /2 = 10 \cdot 0.05 \cdot 0.5^2 /2 = \pm 0.0625m$$

That is the relative position error will be around: 0.0625/10 ≈ 0.63%

The above calculation assumes that the movement is along a single global axis only. In fact the movement direction on a flat path is the resultant of global x- and y-axis components. Thus the acceleration along the movement direction is calculated as:

$$a_{md} = \sqrt{a_x^2 + a_y^2} \quad (1)$$

where a_{md}, a_x and a_y represent the accelerations along the movement direction, global x-axis and global y-axis respectively. The combined uncertainty u_{amd} in a_{md} can be calculated in terms of the uncertainties of a_x and a_y as:

$$u_{amd} = \sqrt{(\frac{\partial a_{md}}{\partial a_x})^2 u_{ax}^2 + (\frac{\partial a_{md}}{\partial a_y})^2 u_{ay}^2 + 2(\frac{\partial a_{md}}{\partial a_x})(\frac{\partial a_{md}}{\partial a_y}) u_{axay}} \quad (2)$$

where u_{axay} is the covariance between a_x and a_y. Assuming no correlation between the uncertainties of the variables a_x and a_y yields:

$$u_{amd} = \sqrt{a_x{}^2/(a_x^2 + a_y^2) u_{ax}^2 + a_y{}^2/(a_x^2 + a_y^2) u_{ay}^2} \quad (3)$$

Hence for the case that u_{ax} approximately equals u_{ay} we have $u_{amd} = u_{ax}\sqrt{2}$ which results in 0.9% of position error for the numerical values given above. On the other hand for some sensors the offset on one axis is extremely small compared with the offset on the other one. For these cases the movement path could be directed to the appropriate global axis to reduce the total error.

3.3 Experimental Set-up & Experiments Conducted

Our tests have pointed out that one of the best locations is the front part of the foot to detect that the foot rests. Our experimental results show that a value around 0.15m/sec^2 for the resultant instantenous acceleration of all the three axes for successive 5 samples can be defined as a threshold that the foot is motionless. Figure 1 pictures a sample for free acceleration data together with the visual information of the resting intervals of foot that they are marked as pulses in black. The corresponding velocity graphs for both the uncorrected and corrected data are presented in Figure 2. Figure 3 demonstrates the uncorrected and corrected data for the corresponding position.

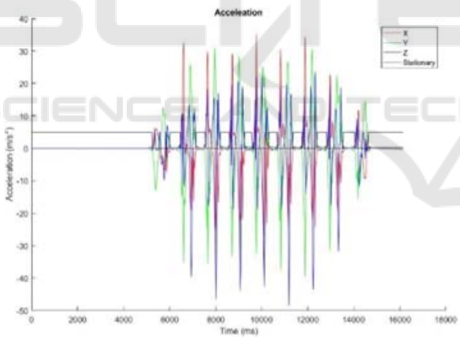

Figure 1: Sample free acceleration data.

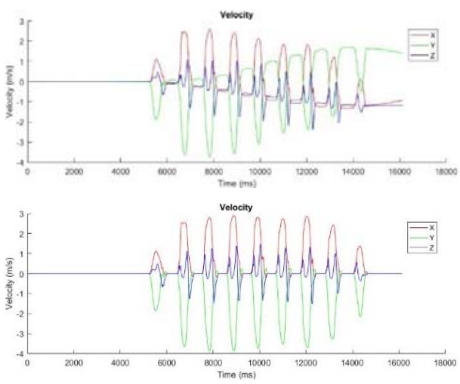

Figure 2: Velocity data (Above: uncorrected, below:corrected).

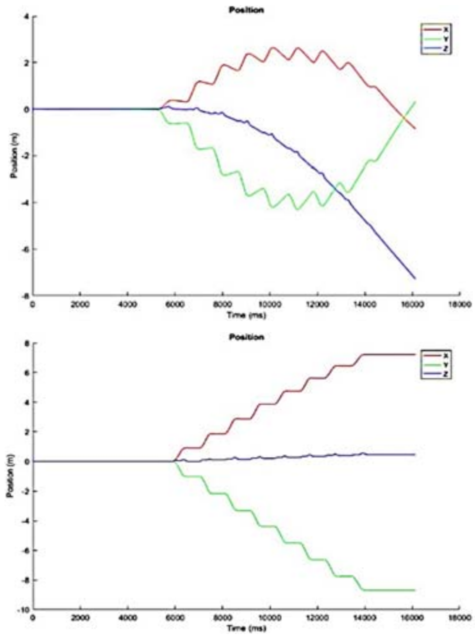

Figure 3: Foot position data (Above: uncorrected, below: corrected).

For the gait/balance analysis the position and/or direction of the foot only wouldn't give enough information. There is also need for information from other parts of the body to monitor the sway of the person. In this manner we have to know about the movement of the knee especially while the related foot rests. This obviously requires that the data received from the sensor located around the knee is reliable. On the other side for a healthy person the knee never rests during the walk. So, the offset correction of the sensor around the knee cannot be performed by resetting the velocity offset at certain intervals the same way we did it with the foot. So there is need for another reference for correction of the knee position information. In our study the following recognition helped us to find a suitable method to apply: The ith step length l_i (i>1) of a foot is approximately the same as the difference between the positions of the related knee corresponding to instants when the pivot foot leaves (i-1)st and ith restings (Figure 4). This explanation holds for both the x- and y- axis position values. So we correct the knee position every gait cycle by resetting the velocity offset according to the recognition explained above. Figure 5 describes the flow diagram for position-data correction of the knee.

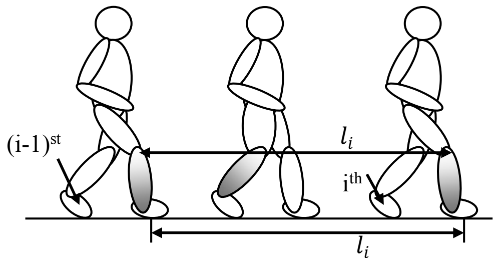

Figure 4: References to correct knee position data.

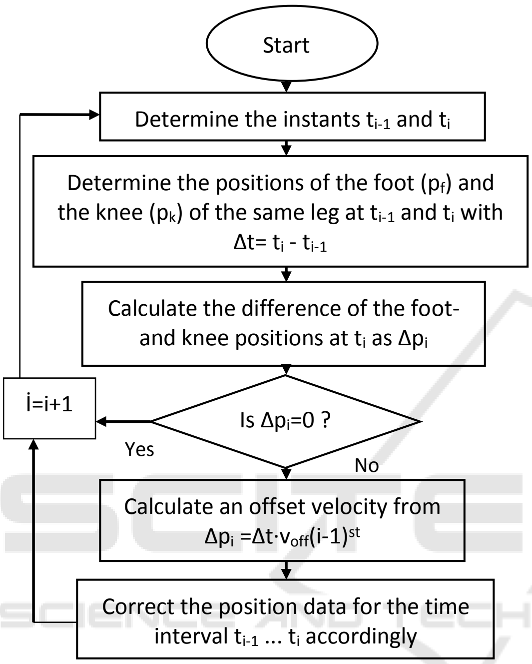

Figure 5: Flow diagram for position-data correction of the knee.

Figure 6 shows the locations of inertial sensors on the body.

Figure 6: Sensor locations on the body.

Figure 7 & 8 picture a sample uncorrected and corrected velocity and position graphs -together with the corrected position graph of the pivot foot-respectively.

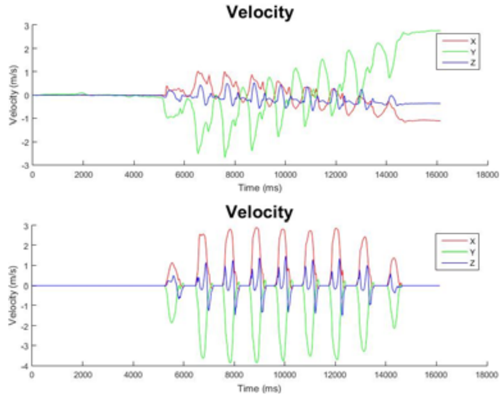

Figure 7: Knee velocity graphs (Above: uncorrected, below: corrected).

4 EXPERIMENTAL RESULTS AND COMMENTS

We collected data from 42 people with 33 being healthy and 9 suffering from several problems to cause balance disorder. The mean ($\bar{l}$) and the standard deviation (σ_l) of the measurements of the path length via the sensors is calculated as 11.41m and 36cm respectively using the formulae

$$\bar{l} = \frac{1}{42}\sum_{i=1}^{42} l_i \tag{4}$$

$$\sigma_l = \sqrt{\frac{1}{41}\sum_{i=1}^{42}(l_i - \bar{l})^2} \tag{5}$$

Hence the average relative error of the length measurement is calculated as:

$$\varepsilon_l = \frac{l_t - \bar{l}}{l_t} = 0.8\% \tag{6}$$

where the true length is $l_t = 11.5m$.

The average error is acceptable; but the standard deviation is a little large. We bring the following comments on the results:

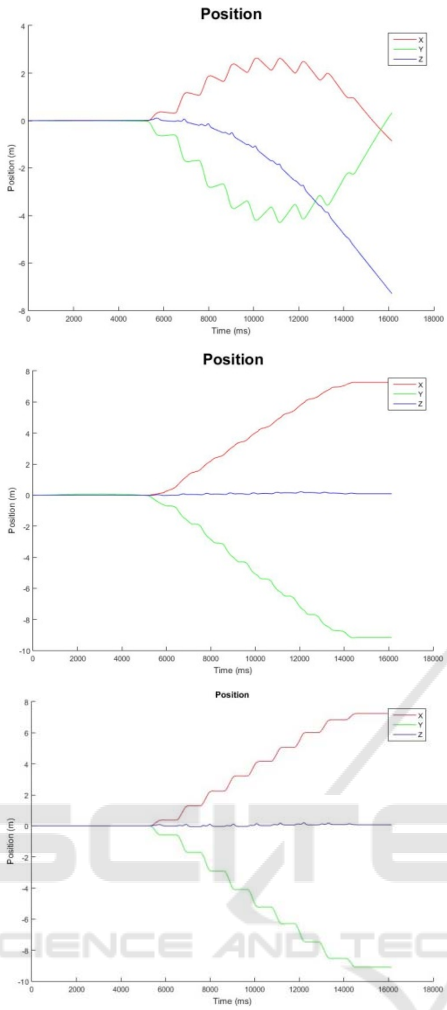

Figure 8: Knee position (Above: uncorrected, mid: corrected) & pivot foot position graphs.

Comparing the results with those achieved by the methods used for acceleration data correction points that the proposed method gives much higher accuracy than optical mouse- or system identification based methods. This is obviously because we reference the ground connection of the foot where the velocity is zero; thus, having a reference to refer to ‘frequently enough’ to avoid accumulation of the error is more effective than relying on calibration for long-term operation.

Besides the drift in acceleration offset following points are also worth to mention to influence the error and the standard deviation in the measurements:

- Error in determination of the resting period of the foot and accordingly filtering the acceleration data.
- Error in observing the start and stop points of the walk.
- Error in calculating the acceleration offset prior to starting the walk that is subtracted from all the instantenous acceleration data.

In our study the sampling rate of the sensors was 100Hz limited by the specifications of the sensor. Increasing this frequency would obviously help for higher accuracy that the offset at the beginning and the resting durations of the foot can be determined more precisely.

5 CONCLUSIONS AND FUTURE WORK

This study is a part of the project where we aim to discover features decribing several sources of balance disorders. In this manner we are interested in certain parameters used for gait analysis such as the change of the difference between the feet positions, step length, sway of the legs etc. These parameters condition the correct determination of foot- and knee positions. In our study we use inertial sensors placed on foot and knee and the position is determined by double integrating the free acceleration data of the related sensor. Since the offset and the drift of the sensor is significantly effective on position determination we propose a method to minimize this effect that we make use of the durations where the foot rests. The results put forth that the proposed method is a satisfactory solution giving reasonable relative error in average; nevertheless the standard deviation still needs some correction.

So far we have applied our method mainly on healthy people (33 out of 42) where the walk path was a straight line. So as future work, first of all we consider to increase the number of subjects suffering from several balance disorders and draw a curved path in order to verify the general applicability of the method. Besides that we plan to develop methods to reduce the standard deviation. In this context we care determining the offset at the beginning more precisely, because it influences all the durations where movement exists. Considering the overall frame of the project we also need to detect the sway of the upper part of the body. So we will investigate for methods to monitor the whole body within acceptable error limits.

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