CYCLOS

PREVENTING LOW BACK PAIN AMONG CYCLISTS USING THE AUTOREGRESSIVE MODEL WITH A REAL-TIME FEEDBACK MECHANISM

INTRODUCTION

Recently, low back pain was rated responsible for the most years lived with disability when all common diseases were considered. Some statistics are –

- Of the 85% of cyclists who report injury every year, 30.3% require medical treatment for low back pain *[The American Journal of Sports Medicine & The International Journal of Sports Medicine]*
- Low back pain due to cycling that ranked as the 6th most burdensome condition in 1990, jumped to the 3rd position in 2010. *[National Institute of Neurological Disorders and Stroke, Maryland]*

BACKGROUND RESEARCH

- Apart from buying the correct bike, interestingly researchers show that muscle fatigue among cyclists worsens their spine posture. *[Cycling Weekly, Time Inc. UK]*
- Repeated stretching and contraction of the Quadratus Lumborum muscle *[Avoiding Low Back Pain as a cyclist, USA]*

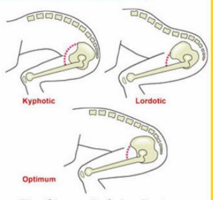

Fig. Change in Spine Posture due to fatigue while cycling (Dalton Articles, Freedom from Pain Institute)

An inappropriate spine posture due to the above mentioned reasons could lead to a Chronic Low Back Pain or a Herniated Fibrous Disc causing pain.

Current Treatments/ Devices

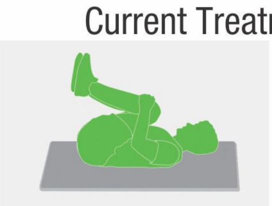

Fig. Physiotherapy (National Health Service, UK)

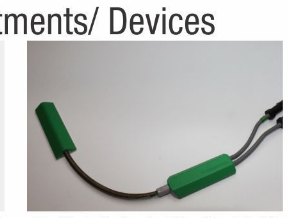

Fig. Electro Goniometer (Biometrics Ltd, UK)

Treatment post injury
Slow recovery

Bulky, Expensive $500+
Can be used only in a Gait Lab

PURPOSE

- Provide an inexpensive solution which prevents low back pain at its source itself rather than treatment after injury
- Extend the usability of the device for a real time experience instead of a clinical environment

SUMMARY

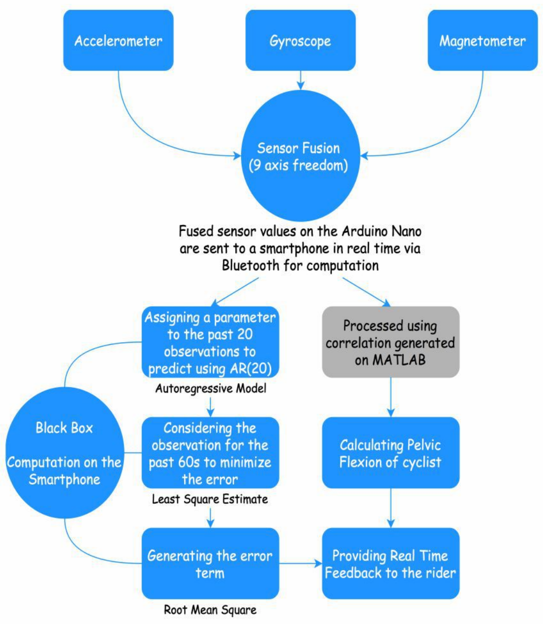

Fig. Process Flow

HYPOTHESIS

- A combination of motion sensors can be used to detect the pelvic flexion when placed at L1, the junction of stiff thoracic spine and mobile lumbar spine
- Statistical Models can be used to differentiate between the change in inclination of road and the change in posture detected from the same sensor values to avoid false alarms
- The Autoregressive Model will help provide real time feedback about their posture to cyclist to prevent low back pain

MEASURING LUMBAR FLEXION

Final Design

- A 9 axis Inertial Measurement Unit (IMU) – Accelerometer, Gyroscope and Magnetometer which is Bluetooth enabled to send values in real time
- The device runs on a rechargeable 3.7v 1000 mAh Lithium ion Polymer battery
- The computation and feedback mechanism is carried out on the smartphone

The device is placed on the first vertebrae of the lumbar region (L1) at the junction of mobile lumbar spine and stiff thoracic spine to measure the spine flexion

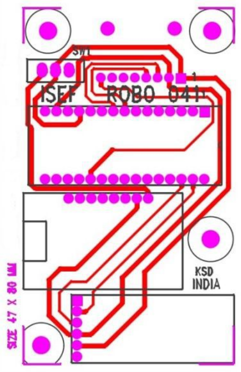

Fig. Final Design (Taken by me)

Correlation of sensor values to pelvic flexion of the cyclist

Pelvic girdle fused with the tailbone results in a change in pelvic flexion for a change in lumbar flexion.

- Markers placed on the Anterior Superior Iliac Spine and Posterior Superior Iliac Spine to measure pelvic flexion
- Subjects flex their spine forward and raw data captured
- Data processed on MATLAB to generate correlation of Sensor Values with increasing pelvic flexion

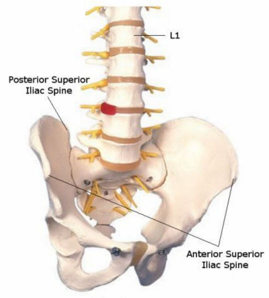

Fig. Setup

In order to generate a correlation, the sample size consists of 37 participants finally generating a Pearson Correlation Coefficient of 0.862.

Black Box - The Autoregressive Model combined with the Least Square Estimate and Root Mean Square

While testing on roads, the fused sensor values were affected by the uneven terrain and the inclination of the road leading to false alerts. These false alerts are avoided with the help of moving calibration of the Autoregressive Model combined with the Least Square Estimate and Root Mean Square.

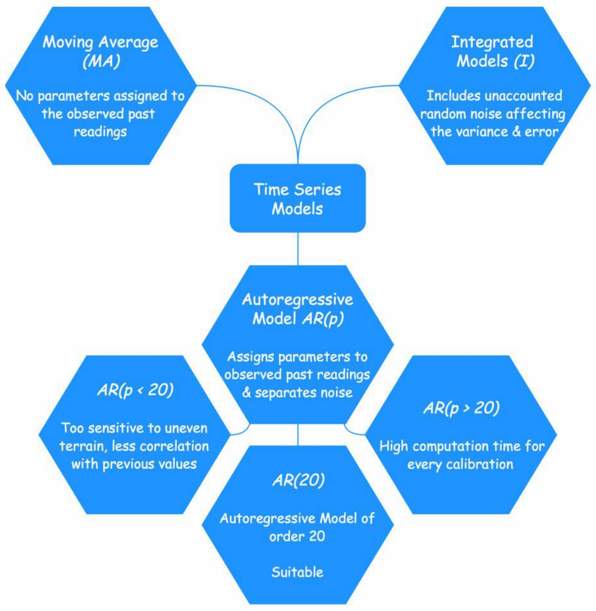

Fig. Suitable Time Series Model

The Autoregressive Model

Many time series exhibit serial correlation suggesting that past observations each with a varying weightage will help predict and compare the current observations. The notation *AR(p)* indicates an Autoregressive Model of order p which is defined as

$$X_t = \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

where φ_i are the parameters assigned to past observations signifying the weightage of that particular reading, and ε_t is the white noise with a zero mean. Therefore, for example AR*(1)* is given by

$$X_t = \varphi_1 X_{t-1} + \varepsilon_t$$

Post experimentation, it is deduced that the X_t will be calculated using *AR*(20) and every calibration is based on the past 60s, therefore

$$X_{21} - \sum_{i=1}^{20} \varphi_i X_i = \varepsilon_{21}$$

$$X_{22} - \sum_{i=1}^{20} \varphi_i X_{i+1} = \varepsilon_{22}$$

$$X_{60} - \sum_{i=1}^{20} \varphi_i X_{i+39} = \varepsilon_{60}$$

Integration with Least Square Estimate and Root Mean Square

To be able to minimize the noise and find the values of $\varphi_1, \varphi_2, \varphi_{20}$ we use the least square estimate. Squaring on both sides,

$$\left(X_t - \sum_{i=1}^{p} \varphi_i X_{t-i}\right)^2 = (\varepsilon_t)^2$$

$$\left(X_{21} - \sum_{i=1}^{20}\varphi_i X_i\right)^2 + \left(X_{22} - \sum_{i=1}^{20}\varphi_i X_{i+1}\right)^2 + \left(X_{23} - \sum_{i=1}^{20}\varphi_i X_{i+2}\right)^2 \dots + \left(X_{60} - \sum_{i=1}^{20}\varphi_i X_{i+39}\right)^2 = \varepsilon_{21}^2 + \varepsilon_{22}^2 + \varepsilon_{23}^2 \dots + \varepsilon_{60}^2$$

To minimize the parameters, the equation above is differentiated with respect to $\varphi_1, \varphi_2, \dots \varphi_{20}$ and equated to 0 –

With respect to φ_1: $$2\left(X_{21} - \sum_{i=1}^{20}\varphi_i X_i\right)^2 (X_1) + 2\left(X_{22} - \sum_{i=1}^{20}\varphi_i X_{i+1}\right)^2 (X_2) + 2\left(X_{23} - \sum_{i=1}^{20}\varphi_i X_{i+2}\right)^2 (X_3) \dots + 2\left(X_{60} - \sum_{i=1}^{20}\varphi_i X_{i+39}\right)^2 (X_{40}) = 0$$

With respect to φ_2: $$2\left(X_{21} - \sum_{i=1}^{20}\varphi_i X_i\right)^2 (X_2) + 2\left(X_{22} - \sum_{i=1}^{20}\varphi_i X_{i+1}\right)^2 (X_3) + 2\left(X_{23} - \sum_{i=1}^{20}\varphi_i X_{i+2}\right)^2 (X_4) \dots + 2\left(X_{60} - \sum_{i=1}^{20}\varphi_i X_{i+39}\right)^2 (X_{41}) = 0$$

With respect to φ_{20}: $$2\left(X_{21} - \sum_{i=1}^{20}\varphi_i X_i\right)^2 (X_{20}) + 2\left(X_{22} - \sum_{i=1}^{20}\varphi_i X_{i+1}\right)^2 (X_{21}) + 2\left(X_{23} - \sum_{i=1}^{20}\varphi_i X_{i+2}\right)^2 (X_{22}) \dots + 2\left(X_{60} - \sum_{i=1}^{20}\varphi_i X_{i+39}\right)^2 (X_{59}) = 0$$

Solving the above equations simultaneously to deduce the variables $\varphi_1, \varphi_2, \dots \varphi_{20}$ which can then be used to calculate the expected error ε_t using the Root Mean Square –

$$\varepsilon = \sqrt{\frac{\varepsilon_{21}^2 + \varepsilon_{22}^2 + \varepsilon_{23}^2 \dots + \varepsilon_{60}^2}{40}}$$

Knowing $\varphi_1, \varphi_2, \dots \varphi_{20}$ and ε_t is then used to calculate predicted value of X_t as X_{est} using the equation. Therefore, the cyclist is warned when

$$X_t \notin [X_{est} - 3\varepsilon, X_{est} + 3\varepsilon]$$

RESULTS

Selecting the order of the Autoregressive Model

Multiple sets of the same motion sensor values were computed through the Autoregressive Model with 7 varying orders ranging from 4 to 28 at an interval of 4 and recorded the corresponding error terms from 42 subjects

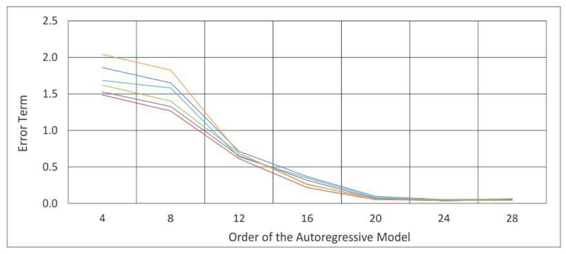

Fig. Graph of Average Error term plotted against the order of the Autoregressive Model

It is noticed that the error term of the Autoregressive Model is minimized when the order is 20, or otherwise requires more computation time for higher orders. The three case experiment to assess the effect of change in terrain on the parameters and variance of the Autoregressive Model. Note that the initial values are used for calibration of the model

Case 1 – Flat terrain

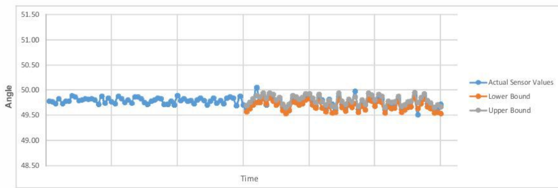

Fig. Graph pattern of processed upper and lower bound through the AR(20) on a flat terrain

Case 2 – Increase in inclination of road

Fig. Graph pattern of processed upper and lower bound through the AR(20) on an inclined terrain

It is essential to avoid false alarms due to the incline of the road, which is achieved by adjusting the error bounds

Case 3 – Uneven Terrain

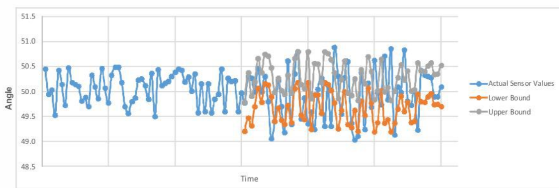

Fig. Graph pattern of processed upper and lower bound through the AR(20) on an uneven terrain

The error term fluctuates too much due to the oscillating motion sensor values that aren't able to normalize owing to the uneven terrain

CONCLUSION

- Cyclos provides reliable real time feedback, avoiding false alarms due to white noise, to cyclists to prevent low back injuries
- Cyclos is easy to deploy, with the adhesive for placement at L1, and portable so that it can be used on field in comparison to the existing solutions
- Cyclos is a personalized posture coach for endurance cyclists for a back pain free ride

FUTURE SCOPE

- Increase self-learnt personalization with incorporation of parameters such as the flexibility and core strength of the rider
- Support the spine flexion by measuring the tightness of the Quadratus Lumborum muscle
- Considering user feedback to dismiss warnings accounting for the error approximation

Apart from cycling the applications are endless, the feedback mechanism can be used by everyone prone to injuries - people who drive vehicles, who weight train in gyms and office workers doing long hours of desk jobs, the innovation can be used to monitor and correct daily actions.

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- Shumway, Robert H., and David S. Stoffer. Time series analysis and its applications: with R examples. New York: Springer, 2010.