Analysis and Adequate Model Identification for Classic cross-country Ice Skiing Techniques using Vectorial Time-Series Modeling

UT Austin ORI 390R Project

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Abstract

Cross-country (XC) skiing is a famous recreational and competitive sport in many Scandinavian countries, and certain South-East Asian countries (South Korea). The primary techniques in classical type of XC-skiing are diagonal stride, double poling with kick and double poling [1]. Over the years, many rule-based, statistical, and machine learning approaches have been utilized for the identification and classification of these techniques [2]. However, most of the data utilized has been collected in laboratory settings. The rule-based approaches are very time-consuming as cut-offs must be ascertained for kinematic measurements (linear acceleration, angular velocity, angular acceleration) while neural networks are black-boxes which do not allow the analysis of variance and the stability of the trained models [1]. In this study, I address both the limitations. Firstly, I utilize ice-skiing data of South Korean Olympic skiers on flat and natural (uphill and downhill) course. Secondly, I utilize vectorial autoregressive moving average time-series (ARMAX) modeling to identify adequate models for diagonal stride technique for 3 skiers with stability guarantees. Lastly, I also forecast the future values of angular velocities for the skiers to illustrate the unique forecasting power that neural networks and rule-based approaches lack.

1 Key Information to include

- Mentor: Prof. Dragan Djurdjanovic, UT Austin
- Source of data: Korea Advanced Institute of Science and Technology

2 Introduction

2.1 Cross-country (XC) skiing

Cross-country (XC) skiing is a whole-body exercise endurance sport, which requires prolonged complex cyclical motions performed using skis and poles on the snow [1]. There are two main styles in XC-skiing: the classical and the skating style. The classical style can be performed both on prepared trails with pairs of parallel grooves cut into the snow or on natural undisturbed snow whereas the skating style is generally performed on firm and smooth snow surfaces. Each of the classical and skating styles have four techniques or gears. These are diagonal stride (DS), double poling (DP), push-off (P-Off), and kick-double poling (KDP) for the classical style, and V2 skate (V2), V2A skate (V2A), V1 skate (V1), and free skate (FS) for the skating style, respectively.

In XC-skiing, the performance of the skiers depends on the biomechanical and the physiological aspects of the motions of the body parts and the sequence in which the skiing techniques are performed on the uphill and downhill tracks (commonly known as a natural course) and flat tracks (flat course). As the results of the skiing races can be determined by time steps as small as a few milliseconds, it becomes imperative for the professional coaches to understand both these aspects of XC-skiing to recommend an improved set of techniques for optimizing the performance of the skiers.

Body worn sensors, particularly the inertial sensors have recently emerged as a convenient substitute for such systems due to their small size, light weight, and low cost [4,5]. Inertial sensors are sensors based on inertia and relevant measuring principles. In general, inertial sensors include gyroscopes used for measurements of the sensor's angular velocity and accelerometers for measurements of linear acceleration. These sensors can sample at high frequencies and are easily attached to the skier's body without interfering with the natural motion during skiing. This ease of use has made it possible to carry out experiments that require sensor data outside the controlled environment of the laboratory and provide a more realistic analysis of the task at hand. Marshland et al. [3] were the first to demonstrate this potential of body worn microsensors in the identification of XC-skiing techniques by plotting acceleration and angular velocity curves for eight athletes for both the classical and skating techniques. By visual inspection of the cyclical patterns in these plots, they concluded that all the classical and skating techniques can be clearly identified for each skier, with certain variations unique to each skier.

2.2 Vectorial Time Series modeling

A time series is a series of data points indexed in the order of time. Generally, the indices are uniformly spaced, and the data points represent a physical quantity like velocity, acceleration, force, etc. or some other entity of interest like price of a stock. Time-series modeling is a statistical methodology used to identify trends and patterns in the time series. This analysis is performed by fitting an auto-regressive model with moving average parts. The autoregressive part utilizes observations from previous time steps as input to a regression equation to predict values at next time steps. The moving-average part helps in minimizing the fluctuations in the time-series, known as smoothing the time-series.

When we observe several related time-series in parallel, their collection is known as a vectorial time series (or a multivariate time-series). Multivariate time-series are of considerable interest in a variety of fields such an engineering (e.g.: in the analysis of current and voltage over time), physical sciences (particularly in geophysics and metrology), economics, and finance (values of related stocks over time). The basis methodology of modeling a vectorial time-series, however, is more or less like a scalar (univariate) time series.

3 Data Acquisition

The dataset consists of the kinematical data of 3 South Korean Olympic skiers on flat and natural course using XSens inertial measurement units (IMUs). The 17 IMUs were attached to various locations on the body of each skier as shown in the figure below.

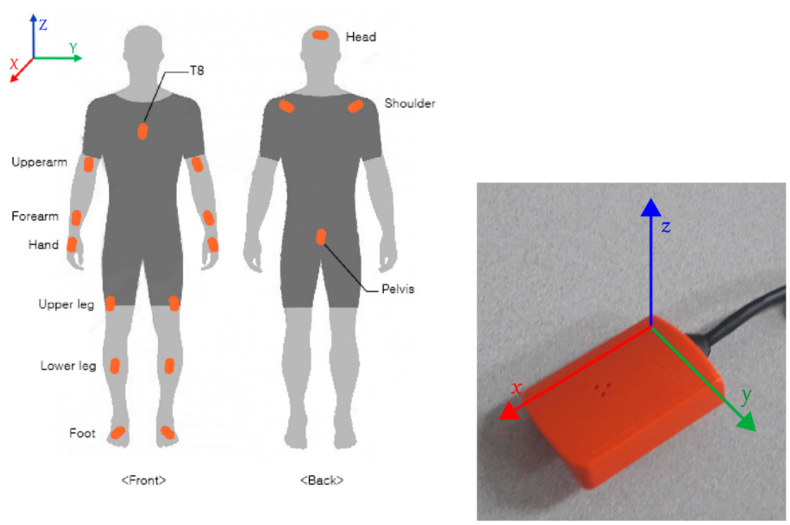


Figure 1. (**Left**) Front and back view of the position of 17 inertial motion trackers that are attached to the Xsens bodypack worn by the skiers. (**Right**) One Xsens inertial motion tracker depicting the local *x*, *y*, and *z* axes.

Each sensor consists of a gyroscope, an accelerometer and a magnetometer. Each sensor samples angular velocity, linear acceleration and magnetic field at 240 Hz along the x, y and z axes, thus giving 17*3*3 =153 time series for each skier. The angular velocity and linear acceleration for the classical XC-skiing techniques are illustrated in Figure 2.

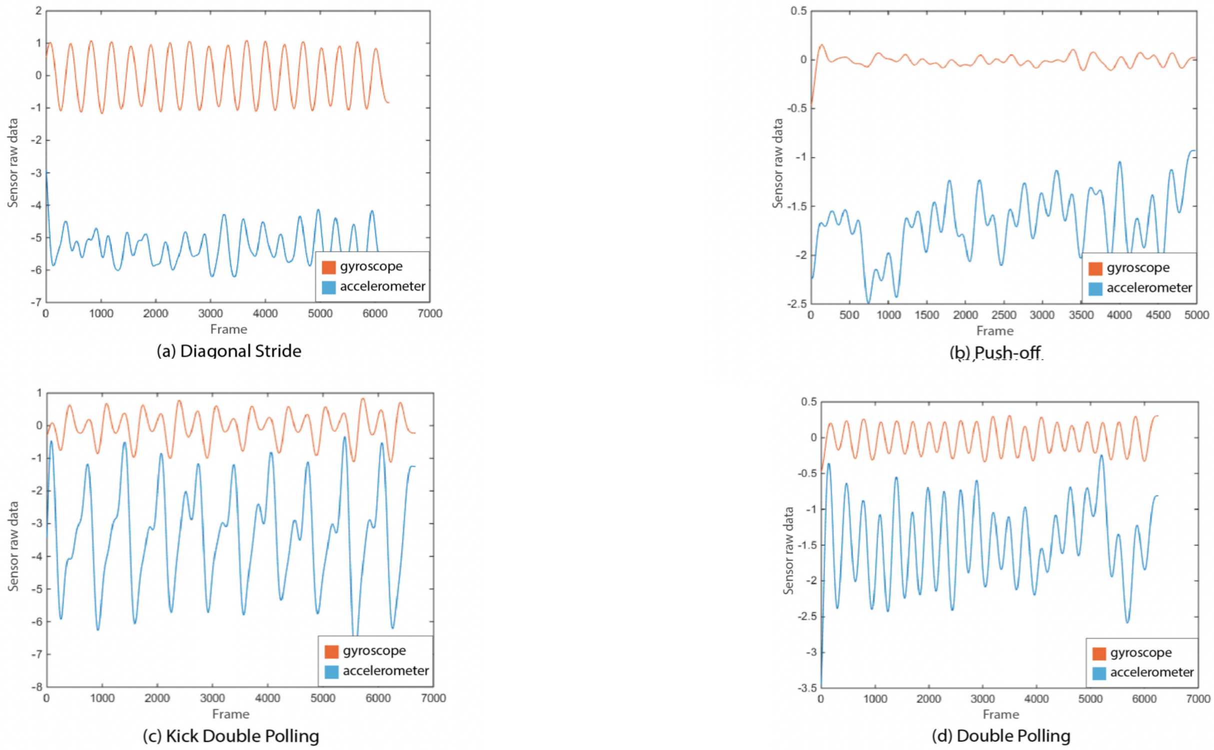


Figure 2. Comparison of the cyclic patterns in the *z*-axis (anteroposterior direction: normal to frontal plane) angular velocity and linear acceleration data (from a motion tracker on the flat surface of the shin bone of left leg) for the classical XC- skiing techniques.

As is clear from the figure, angular velocity data, which is obtained via the gyroscope, shows more easily identifiable cyclic patterns as compared to linear acceleration data, which comes from the accelerometer. This is the primary reason for selecting angular velocity for our modeling strategy.

3.1 Diagonal Stride

For the purpose of this study, I use the angular velocity data for the diagonal stride technique for each of the 3 skiers. The first 2 skiers, referred to as skier 1 and skier 2 performed the techniques on flat course, and skier 3 performed it on natural (uphill and downhill) course. In diagonal stride, opposite arms and legs swing at the same time (left leg with right hand and vice versa). In this sense, it is very similar to running. It can be performed both on natural course as well as on a flat course. As the technique is intuitive and simple to learn, it is the first technique that is taught to an amateur skier.

Figure 3. Diagonal Stride: generating motion using left pole and right leg (left), both poles (center) and right pole and left leg (right)

4 Approach

There are a total of 51 time series for the angular velocity data for each skier. I have used the sports biomechanical configuration of sensors – both hands, both feet and the pelvis sensors. The z-axis angular velocity of the sensor in the pelvis region is used as the output, and other 14 time-series as the input. The z-axis angular velocity is used as the output as it is closer to the center of mass of the body. I fit ARMAX(n,n-1) models of increasing orders, and select the best model using the Akaike Information (AIC) criterion.

5 Results

ARMAX models are fit to the angular velocity data of each skier and the adequate model for each skier based on the AIC criterion is given in Table 1. These are the baseline models in the sense that future researchers can use the order of these models as a starting point for their analysis of the diagonal stride technique.

Skier	Adequate ARMAX model order	R^2 value Explained variance ratio	Mean Squared Error
1 - Flat Course	27, 26	0.9903	1.01e-06
2 - Flat Course	23, 22	0.9867	6.01e-06
3 - Natural Course	17, 16	0.9156	1.67e-05

Table 1. Adequate ARMAX model, R^2 and MSE for the 3 skiers based on Akaike Information Criterion

5.1 Analysis of residuals and autocorrelations

The figures below show the residuals of the output time series and its autocorrelations for up to 20 lags.

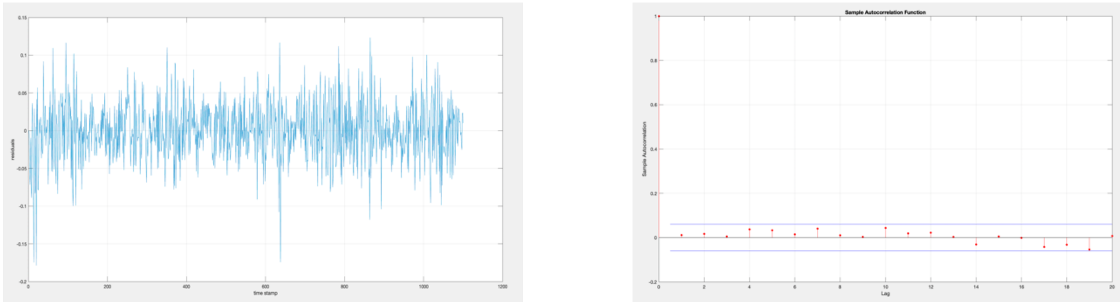


Figure 4: Residuals plots for output time series for skier 1 (left) and autocorrelations of residuals up to 20 lags (right)

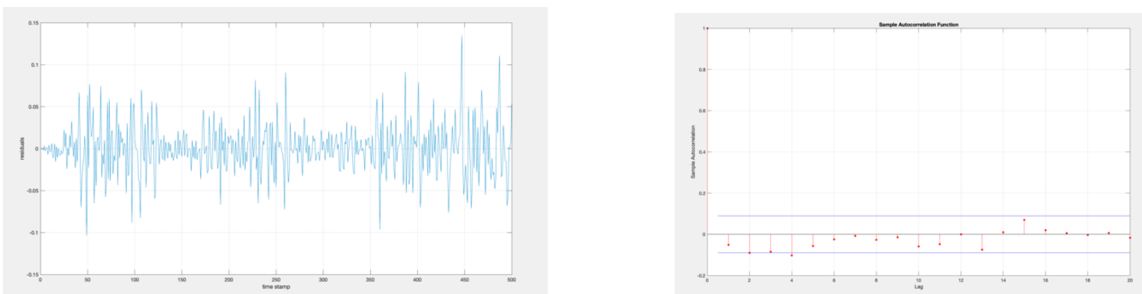


Figure 5: Residuals plots for output time series for skier 2 (left) and autocorrelations of residuals up to 20 lags (right)

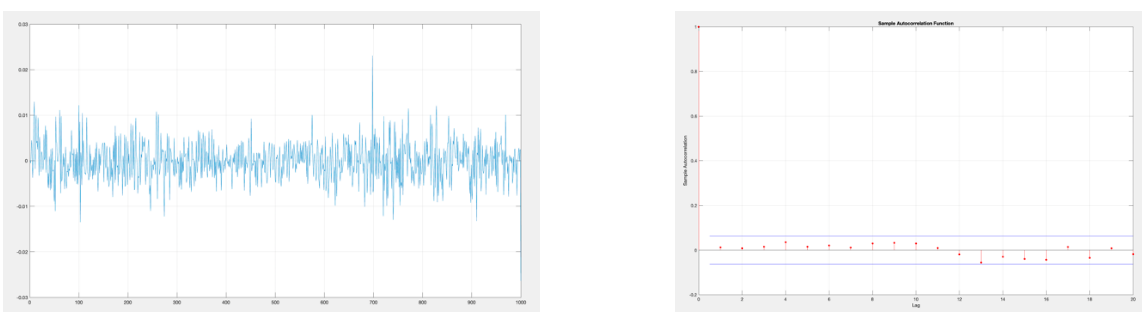


Figure 6: Residuals plots for output time series for skier 3 (left) and autocorrelations of residuals up to 20 lags (right)

As is clear from the above plots, the residuals for the adequate models do not have any trend. The gold standard for determining whether residuals are uncorrelated is no correlation between the residuals. We observe that the autocorrelations are well within the 95% confidence interval around zero, thus implying that the residuals are, in fact, uncorrelated. This means that the ARMAX models are adequate for the respective skiers.

6 Stability Analysis

I plotted the roots of the autoregressive parts of the ARMAV models for each skier. If all the roots are inside the circle, the model is stable, otherwise unstable. As such, only the model for skier 3 (natural course) was found to be stable. Figure 7 shows the roots for the 3 models.

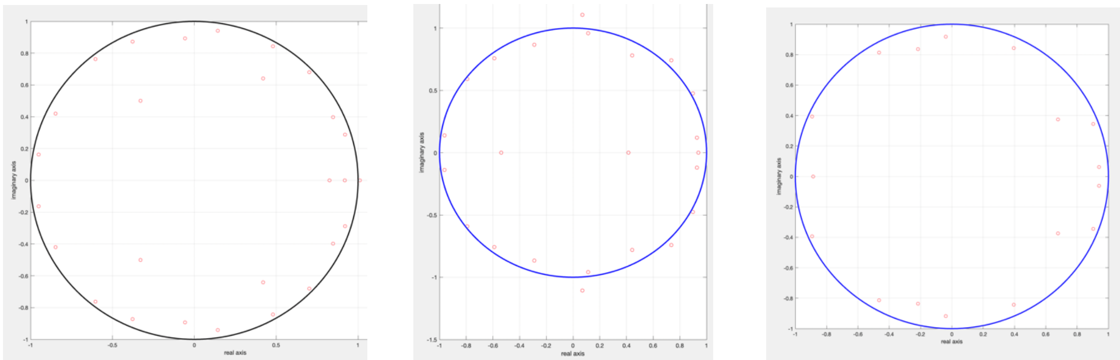
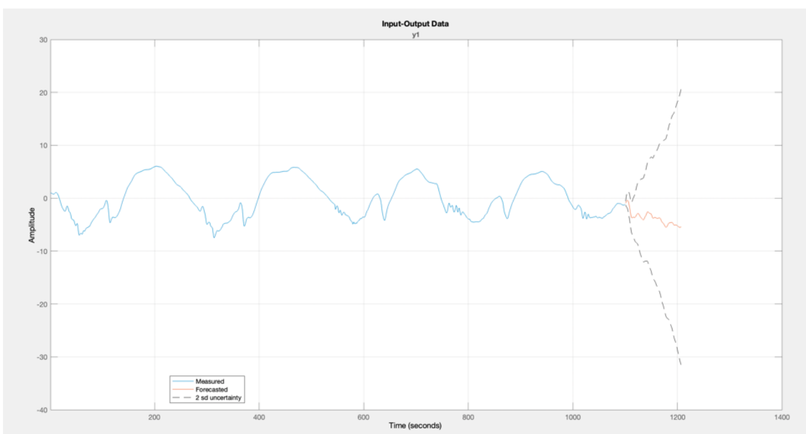


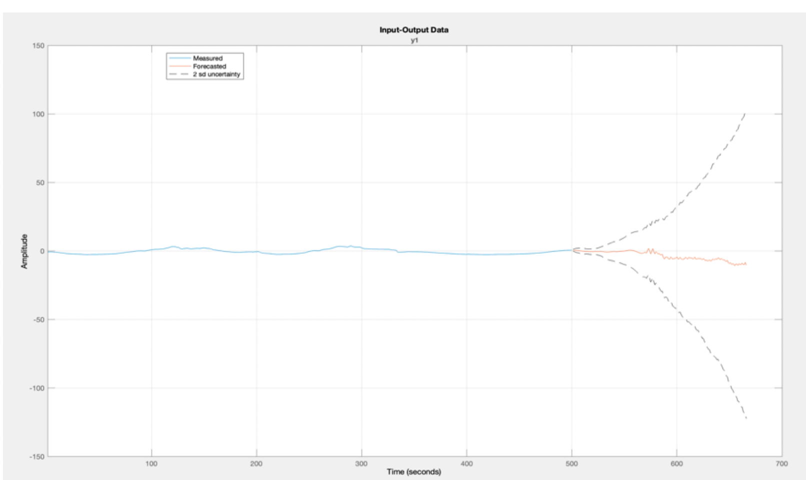
Figure 7: Roots of the autoregressive parts of the ARMAV(27, 26), ARMAV(23 22), and ARMAV(17, 16) models for skier 1, 2 and 3 respectively. Only model 3 is found to be stable.

7 Forecasting

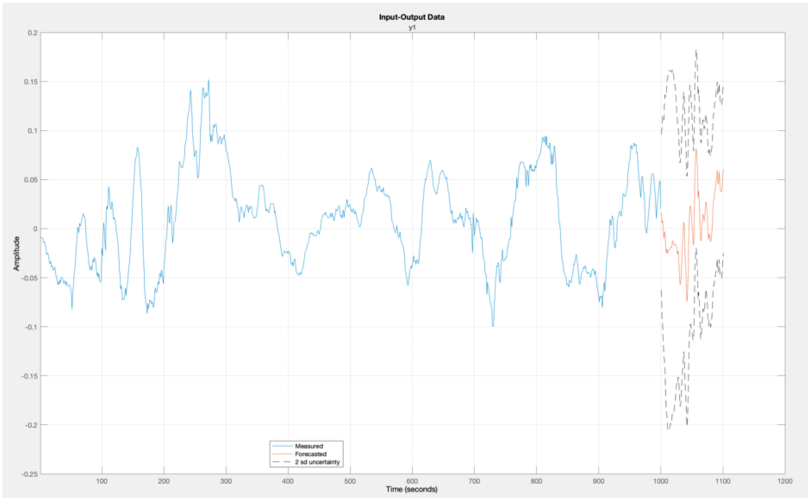
I now perform forecasting of the z-axis angular velocity of each skier using the fitted adequate models. Model forecasting is not the most important use case of my modeling; however, I present the forecasts for the sake of completeness of time-series modeling. The forecasted values and a 95% confidence around them for all the 3 skiers are shown in Figure 8.



(a)



(b)



(c)

Figure 8. Forecasted values for the z-axis angular velocity of the sensor attached to the pelvis region for (a) skier 1 (b) skier 2 (c) skier 3

8 Conclusion

In this study, I found adequate models for diagonal stride XC-skiing technique for 3 skiers – 2 of which performed the technique on flat course and 1 on a natural course. I utilized only the angular velocity data for the sports biomechanical configuration of sensors – both hands, both legs and the pelvis. The adequate models were found to be ARMAV(27, 26), ARMAV (23, 22) and ARMAV(17, 16) for the 3 skiers respectively. Though the analysis is exhaustive for this one technique, a natural extension of this study is to perform the same analysis for other 3 classical XC-skiing techniques. In this study, primary focus has been on the fitting of an adequate model for the skier and conducting stability analysis and forecasting for the same skier. In a future study, one could fit the model for one skier, and perform forecast for another skier to check how well the model transfers from one skier to the other.

9 Acknowledgements

I would like to acknowledge the constant support and constructive feedback provided by Prof. Dragan Djurdjanovic throughout the semester. I would also like to acknowledge the feedback and ideas provided by Rishi Aneja, another student in the same class.

10 References

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