Title:

Prediction of level of drowsiness using an adaptive Geometric Brownian Motion model, with application to drowsy driving accident prevention

Author(s):
Pouyan Ebrahimbabaie, Jacques G. Verly

Institute(s):
Department of Electrical Engineering and Computer Science, University of Liège, Liège, Belgium

Introduction:

Existing drowsiness monitoring systems appear to compute a level of drowsiness (LoD) at the present time based on data up to it. An LoD so produced is not the value of the LoD now. Even if it were, an alert based on it would generally come too late. It is thus paramount that future systems predict the value of the LoD some time-interval ahead in the future. Here, we show that one can produce excellent predictions a chosen number of seconds ahead.

Materials and Methods:

We recently showed that **Geometric Brownian Motion** (**GBM**) excellently models LoD signals. Here, for each LoD signal considered, we use two prediction approaches: we compute a GBM model either once for the whole signal, or repeatedly for the sub-signal corresponding to each position of a fixed-length, sliding window extending up to the present. Obviously, this requires that the corresponding (sub-)signal be GBM, i.e. that the logarithms of the ratios of successive values be normally distributed and independent.

Results:

We used an eyeglass-based photooculographic system developed in our group that produces validated LoD signals. We had 17 healthy subjects perform PVTs at 3 different states of sleep deprivation, and got 51 signals, each with 110 samples produced every 5 sec. Each window is 55 sample long and stepped by 1 sample. Predictions are made 4 samples (20 seconds) ahead. For comparison, it takes a 60-mph truck 6 seconds to leave its lane.

Applying the above normality and independence conditions, we established that all 51 signals and 17 sub-signals - each in one randomly selected window for each of the 17 subjects - were all GBM. In operation, one would likely assume that all (sub-)signals are GBM (as established in studies such as this one). For each of the 51 signals, we proceeded as follows.

For the fixed model, we computed its parameters once using the full signal, and used them to compute directly all predicted values 4 samples ahead. For the adaptive model, we computed its parameters for each position of the window and used them to compute the (single) predicted value 4 samples ahead. In each case, we thus produced a prediction signal time aligned with the true signal.

We checked the prediction quality visually by comparing the predicted values and their 95% confidence levels to the known, true values: for both approaches, the predictions were all remarkably close to the truth. We did not notice significant difference between the fixed and adaptive approaches; however, the fixed one uses twice as many samples to compute the model and is not usable operationally.

Conclusions:

The very preliminary work reported here indicates that the GBM appears useful for predicting future LoD values, including adaptively using a moving estimation window. The present work uses very short signals (110 samples), so that one should expect even better results in real operation, where the signals processed would be much longer, allowing for finer predictions.

Acknowledgements:

We express our gratitude to our colleague researchers who helped collecting the data.