Monitoring Quality for the GPS coordinates in Real Time

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Abstract

ThisworkexaminestheapplicationoftheStatisticalProcessControlformonitoringthequalityofGPS-coordinatetimeseriesinrealtime.Qualitycontrolisconstrainedtomonitoringthelocation(i.e.,mean value)andscale(i.e.,accuracy)oftheavailabledatainone-dimension.

ThedetectionoffailuresorchangesofsmallmagnitudeinGPScoordinatesolutionsiscriticalfor applications requiring continuous and reliable results. Examples include real-time deformation monitoringfordams,high-risebuildings,bridges,earthsurfacetectonicmovements,landslides,etc.

ControlchartsareimplementedasmodulesinasoftwarepackagebeingdevelopedattheCreteTech University, Greece. Thesoftware has been designed tomonitordata in realtimeandtriggersalarms whenever predefined critical valuesareexceeded.Theconventionalcumulativesumsandtheadaptive CusumshavebeenappliedtoReal-Time-KinematicGPSdata,asproducedinanexperiment.Anabrupt shift indatahasbeenassumedtovarybetween0.5to2standarddeviationsfromatargetmeanvalue. Comparativeresultsshowthatthe conventionalCusumsaresuitable and efficienttoolsinmonitoring qualityoftheRTK-GPSdata.Resultsalsoshowthatthecontrolchartsforthedetectionoflocationshifts shouldalsobeaccompaniedbycontrolchartsontheaccuracy.

Objectives

- *Real-timequalitymonitoring of GPS coordinate time series;*
- *Monitoringthelocation(i.e., mean value)andscale (i.e., accuracy) of the datatodetectchanges of small magnitude;*
- *Use ofadditive shift, auto-regressive and IMA models;*
- *Apply different Quality-Control algorithms;*
- *Implement the algorithms in a software package.*

Why Quality Control?

- *Necessary forapplications requiring automatic and reliable results;*
- *Inferences regarding deformation are not biased and forecasts are reliable;*
- *Applications in real-time monitoring of dams, bridges, high-rise buildings, tectonic movements, landslides, etc.*

Algorithms

Control charts from Statistical Process Control:

- *Conventional Cumulative Sums (Cusum) on mean (location) and on variance (scale);*
- *Self-starting Cusum;*
- *Adaptive Cusum, when shift is unknown;*
- *Exponentially Weighted Moving Average (EWMA);*
- *Moving CenterlineEWMA(IMAmodel).*

Design of Algorithms

- *Generate "monitoring signals (residuals)" to detect changes;*
- *Develop statistical tools to detect shifts & measurement failures;*
- *Estimate magnitude of shift (delta) and time of occurrence;*
- *Quick detection delay (out-of-controlAverage-Run-Length,*

Detection of shifts in GPS

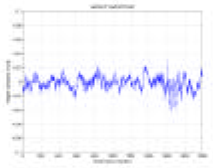
- *Measurement type: Phase, phaserate, pseudo-ranges, (dX, dY, dZ)*
- *Choice of model: Linear model, Kalman Filter, auto-regressive, etc.*
- *Abrupt change type to be anticipated:*
  - Additive shifts, random monitoring signals;

Experiments

1. 24,000 RTK observations (coordinates), 2-second sampling. No intentional movements applied.

2. 6,000 RTK observations (baselinecomponents), 2-second sampling.

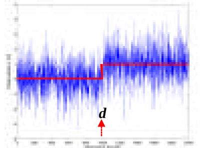
First Experiment



VariationsfortheHeightcomponentforthefirst2,000observations.Samplingintervalis2 seconds.

Data modeling-Random data

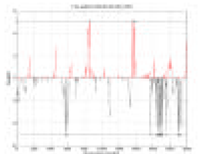
$$X(t) = \mu + \varepsilon(t)$$
$$X(t) = \{\mu + \delta \cdot \sigma_{\varepsilon}\} + \varepsilon(t)$$



AdditiveShiftmodel

Cusum on mean

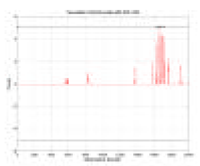
$$S(0)^{(+)}, S(t)^{(+)} = \max\{0, S(t-1)^{(+)} + [\frac{X(t)-\mu}{\sigma}] - k\}$$
$$S(0)^{(-)}, S(t)^{(-)} = \min\{0, S(t-1)^{(-)} + [\frac{X(t)-\mu}{\sigma}] + k\}$$



Thetwo-sidedCusumcontrolchartonlocation,within-controlARL=500(double-sided), *h*=5.071(decisioninterval), *k*= 0.5(referencevalue).Whenthereisanout-of-controlsignal, anasteriskisplotted.

Cusum on variance

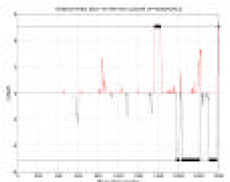
$$V(0)^{(+)} = 0, V(t)^{(+)} = \max\{0, V(t-1)^{(+)} + W(t) - k\}$$
$$V(0)^{(-)} = 0, V(t)^{(-)} = \min\{0, V(t-1)^{(-)} + W(t) + k\}$$
$$W(t) = \frac{\sqrt{|U(t)|} - 0.822}{0.349}$$



Thetwo-sidedCusumcontrolchartonscale,within-controlARL=500(double-sided).

Self-Starting Cusum

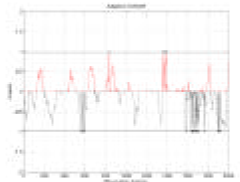
$$S(0)^{(+)} = 0, S(t)^{(+)} = \max\{0, S(t-1)^{(+)} + U(t) - k\}$$
$$S(0)^{(-)} = 0, S(t)^{(-)} = \min\{0, S(t-1)^{(-)} + U(t) + k\}$$
$$U(t) = \Phi^{-1}\left[G_{t-2}\left(\sqrt{\frac{t-1}{t}}Z(t)\right)\right] \quad Z(t) = \sqrt{\frac{t-1}{t}}\left\{\frac{X(t)-\bar{X}(t-1)}{\hat{\sigma}(t-1)}\right\}, t \geq 3$$
$$\bar{X}(t) = \bar{X}(t-1) + \frac{X(t)-\bar{X}(t-1)}{t} \quad \{\hat{\sigma}(t)\}^2 = \frac{W(t)}{t-1}$$
$$W(t) = W(t-1) + \frac{(t-1)}{t}\{X(t) - \bar{X}(t-1)\}^2$$



Theself-startingandrobustifiedCusum,within-controlARL=500(double-sided), *h*=5.071(decisioninterval), *k*= 0.5(referencevalue).

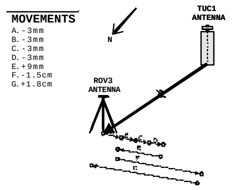
Adaptive Cusum

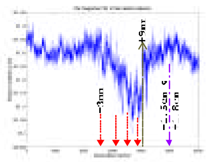
$$SA(0) = 0, SA(t) = \max\{0, SA(t-1) + \frac{Z(t) - [\hat{\delta}(t)/2]}{h[\hat{\delta}(t)]}$$
$$\hat{\delta}(t) = \max\{\delta_{\min}, \lambda Z(t-1) + (1-\lambda)\hat{\delta}(t-1)\}$$



TheadaptiveCusumwithin-controlARL=500(double-sided).

Second Experiment





Variationsofthedistancebetweentheroverandbase GPSstationinthesecondexperiment. Theappliedmovementsoftheroverantennawiththeirmagnitudeandonsettimesare shown.Thetotalnumberofobservationsisabout6000.

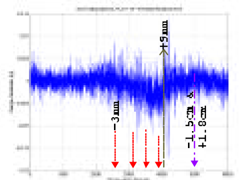
Modeling-Correlated data

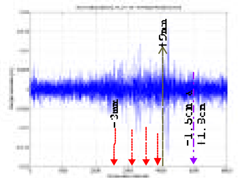
AutoRegressive (1) model

$$X(t) = [\phi_0 + \phi_1 X(t-1)] + e(t)$$

IMA (1,1) model

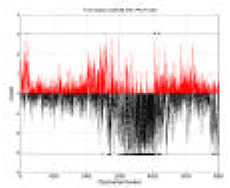
$$X(t) = X(t-1) + e(t) - \theta e(t-1)$$

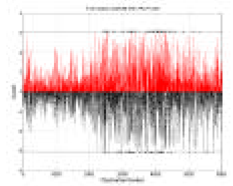




TherangeresidualsafterfittingtheAR(1)andIMA(1,1)model.

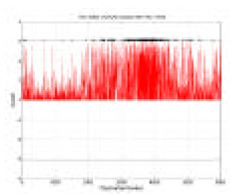
Cusum on mean: residuals

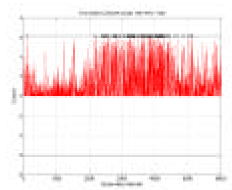




Thetwo-sidedCusumcontrolchartonresidualsforlocationshiftsafterfittingtheAR(1)and IMA(1,1)modelwithin-controlARL=1500(double-sided), *h*=6.1605(decisioninterval), *k*=0.5 (referencevalue).

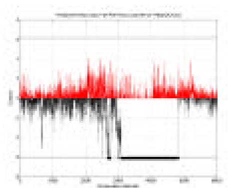
Cusum on variance

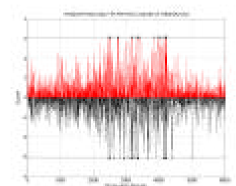




Thetwo-sidedCusumcontrolcharton residualsforaccuracyshiftsafterfittingtheAR(1)and IMA(1,1)model,within-controlARL=1500(double-sided).

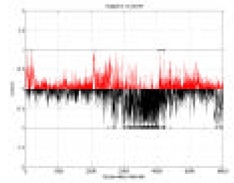
Self-Starting Cusum

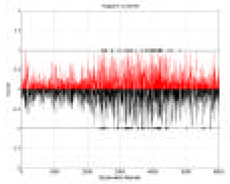




Theself-startingandrobustifiedCusumonresidualsafterfittingtheAR(1)andIMA(1,1) model,within-controlARL=1500(double-sided), *h*=6.1605(decisioninterval), *k*=0.5 (referencevalue).Whenthereisanout-of-controlsignal,anasteriskisplotted.

Adaptive Cusum

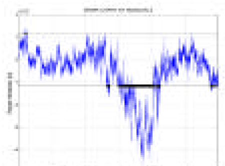


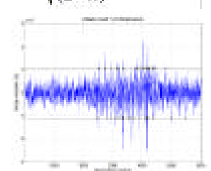


TheadaptiveCusumonresidualsafterfittingAR(1)andIMA(1,1)modelwithin-control ARL=1500(double-sided).

EWMA

$$Z(t) = \lambda X(t) + (1-\lambda)Z(t-1)$$
$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{(2-\lambda)}[1-(1-\lambda)^{2t}]}$$
$$CL = \mu_0$$
$$LCL = \mu_0 - L\sigma\sqrt{\frac{\lambda}{(2-\lambda)}[1-(1-\lambda)^{2t}]}$$

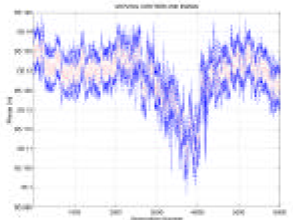




TheEWMAontheresidualsafterapplyinganAR(1)andIMA(1,1)modeltotheoriginaldata.An in-controlARLof1500hasforthetwo-sidedcontrolstatistic, ?=0.1andL=3.215.

IMA model

$$CL = Z(t) = \lambda X(t) + (1-\lambda)Z(t-1)$$
$$UCL_{t+1} = Z(t) + 3\sigma$$
$$LCL_{t+1} = Z(t) - 3\sigma$$



ThemovingcenterlineEWMAchart.Thedesignparametersare ?=1-? andL=3.

Conclusions

- *Cusum charts are able to detect shifts in mean of 0.5 to 2 standarddeviations. Fast detection of small shifts (no delays in detection).*
  Needtoknowanticipated shift a priori.
- *Conventional Cusums couldberobustified to produce fewer false alarms.*
- *Cusum on variance are necessarytomonitorprocess accuracy and reduce falsealarm that may be produced as a consequence ofaccuracydegradation.*
- *Adaptive Cusum continually adjust its form to detect various unknown shifts in mean value.*
- *Control charts could be applied on original observations orresiduals after removing an auto-corellation model.*
- *Process parameters shouldbeestimatedwithcare on calibrated samples or sequentially.*
- *Softwarepackage is being developed at the TUC.*

Acknowledgment: ThisworkhasbeensupportedbytheIRAKLEITOSResearch Fellowships(MIS88727),ThirdCommunitySupportFramework,co-financedby theEuropeanSocialFundFellowships