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Real-time detection of earthquakes through a smartphone-based sensor network

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Abstract. *The Earthquake Network project implements a world-wide smartphone-based sensor network for the detection of earthquakes. The accelerometric sensor onboard each smartphone is used to detect vibrations which are immediately reported to a server. The server analyses the information coming from the entire network and when a quake is detected it is notified to all smartphone users in quasi real-time. In this work we propose and compare two solutions to the detection problem. One solution is based on a likelihood approach and the other is based on filtering.*

Keywords. *Dynamic networks; Real time monitoring; Android; False alarms; Poisson process*

1 Introduction

The Earthquake Network project (`http://www.earthquakenetwork.it/`) implements a world-wide network of smartphones for real-time detection of earthquakes. Smartphone accelerometric sensors detect vibrations which are possibly related to a quake (D'Alessandro and D'Anna, 2013). The data collected by all the smartphones are sent to a server which analyses them to discriminate real quakes from the "background noise". Since collection and data analysis are done in real-time, the earthquake is notified within few seconds. This should allow people living not too close to the epicentre to take measures before their area is affected. In this work, the data acquisition process and two solutions to the detection problem are discussed.

2 Data acquisition

Smartphones which take part to the Earthquake Network project run the Earthquake Network Android application (`https://play.google.com/store/apps/details?id=com.finazzi.distquake`) which collects and reports the data to the server for analysis. The application is able to understand when the smartphone is not in use and thus can be used as a network node. Moreover, the application tries to filter out vibrations which, most likely, are not related to a quake and are induced by other sources of vibrations. A classic control chart is used to detect if the acceleration measured by the accelerometric sensor exceeds a threshold. When this happens, the event is reported to the server along with the spatial position of the smartphone. Additionally, each smartphone reports its state to the server every 30 minutes. This allows to estimate the number of smartphones that are enabled to detect vibrations and thus a possible quake.

3 Earthquake detection

Although the Android application filters some of the vibrations not induced by a quake, many of them are not discriminable and they are reported to the server. Thus, even when quakes are not occurring, the server constantly receives vibration events from smartphones all over the world at random times. When a quake strikes, however, it usually affects a relatively large area and then a given number of smartphones at the same time. The idea is to detect a quake when, for a given area and at a given time, the instant rate of the vibration events exceeds a threshold.

In order to simplify the discussion, we consider here a fixed spatial area (e.g. a city or a small region) and we assume that, when a quake occurs, the entire area is affected. The arrival times of the vibration events are assumed here to be a Poisson process. It follows that the detection problem can be solved either studying the number of events in a given time interval or studying the inter-arrival times of the events. This leads to two approaches which are discussed hereafter.

3.1 A likelihood approach

Let $\{N(t), t > t_0\}$ be the stochastic point process describing the arrival time of the vibration events which is assumed to be a Poisson process with conditional intensity function $\mu(t)$. To define $\mu(t)$, we consider the number of enabled smartphones at time t, namely n_t. Although this quantity is not directly observed at time t, we observe the number ν_t of enabled smartphones sending their "I am alive" signal in the interval $(t - 30\ min, t]$. Hence, n_t can be assumed to be a conditionally independent random variable with distribution parametrized by ν_t and some additional covariates denoted by x_t. In particular, we assume n_t to be conditionally Poisson distributed with expectation

$$E(n_t|\nu_t) = \nu_t \exp\left(\beta' x_t\right).$$

Using this model we aim at detecting the occurrence of a seismic event as soon as possible. To do this we observe that there is a delay in signal transmission and seismic wave displaced perception and we consider the vibration signals in the interval $I_\tau^t = (t - \tau, t]$, for some $\tau > 0$, as signals related to the same earthquake. Extending change point detection techniques which are tailored for permanent changes and asymptotic theory, we consider here $N_\tau^t = N(I_\tau^t)$ signals and a likelihood approach based on the generalized likelihood ratio (GLR) statistic. In order to develop the above mentioned likelihood detector, the log-likelihood of the signals in the interval I_τ^t is introduced

$$\log L(\mu|t,\tau) = \sum_{t_j \in I_\tau^t} \log \mu(t_j) - \mu\left(I_\tau^t\right).$$

where t_j are the arrival times of the events in I_τ^t. Now suppose that, in absence of earthquakes, the process intensity is $\mu^0(t)$ while under a seismic event the process intensity is

$$\mu(t) = \mu^0(t) + \frac{\lambda}{\tau}$$

with $\lambda > 0$ for $t \in I_\tau^t$ and $\lambda = 0$ otherwise. The above log-likelihood has thus the following form

$$\log L(\lambda) = \sum_{t_j \in I_\tau^t} \log\left(\mu^0(t_j) + \frac{\lambda}{\tau}\right) - \mu^0\left(I_\tau^t\right) - \lambda$$

and for a fixed τ, the GLR statistic is given by

$$GLR(\tau,t) = \sum_{t_j \in I_\tau^t} \log\left(1 + \frac{\hat{\lambda}_\tau^t}{\tau\mu^0(t_j)}\right) - \hat{\lambda}_\tau^t$$

where $\hat{\lambda}_\tau^t = \max\left(0, \arg\max_\lambda L(\lambda)\right)$. The above GLR gives an earthquake warning if

$$\sup_{\tau>0} GLR(\tau,t) > h$$

for some threshold h. In particular, since $\mu^0(t)$ depends on n_t, we replace it by its expectation $E\left(\mu^0(t)\,|\nu_t\right) = \alpha\nu_t \exp(\beta' x_t)$.

The second likelihood detector discussed here is based on the efficient score which is given by

$$S(\tau,t) = \frac{\partial}{\partial\lambda}\log L(\lambda)\bigg|_{\lambda=0} = \sum_{t_j \in I_\tau^t} \frac{1}{\tau\mu^0(t_j)} - 1$$

and the score detector gives an earthquake warning if $\sup_{\tau>0} S(\tau,t) > h$ for some threshold h, where μ^0 is defined as above.

3.2 Filtering approach

Let $t_j > t_{j-1}$ for $j = 1,\ldots,n$ the first arrival times of the above $N(t)$ process with $t_0 = 0$. Moreover let $X_j = t_j - t_{j-1}$ be the time between arrivals, which, using local Poisson properties are assumed to be conditionally distributed as negative exponential random variables with mean $\mu(t_j) = E(X_j|\lambda)$, such that

$$\mu(t_j) = \lambda(t_j)^{-1}$$

where λ is given by

$$\lambda(t_j) = \alpha(t_j) + \beta(t_j)\,m(t_j) + e(t_j) \tag{1}$$

In (1), $e(t_j)$ is a white noise process, $m(t_j) = E(\nu_t)$ is a smooth function of time and

$$\alpha(t_j) = \alpha(t_{j-1}) + A(t_j)$$
$$\beta(t_j) = \beta(t_{j-1}) + B(t_j)$$

where A's and B's are the innovations. Note that $\alpha(t_j)$ and $\beta(t_j)$ are not observed and they are estimated using the Kalman filter (see Shumway and Stoffer, 2006). Since $X_j = t_j - t_{j-1}$ are random, the innovations are not iid and their variances are modulated according to X_j. Detection of an earthquake is done monitoring the filtered $\alpha(t_j)$ and $\beta(t_j)$ using, for instance, a control chart calibrated to have a (possibly small) false-detection rate.

4 Discussion

Both the above approaches have pro's and con's. The likelihood approach requires to observe the arrival process over the window $(t-\tau,t]$ and the detection performances are influenced by the choice of τ. If τ is too small, the earthquake can be missed due to possible delays in the transmission from the smartphones to the server. On the other hand, a large τ may produce delays in the detection and notification of the quake. The filtering approach does not require to set the above window and the Kalman update is much faster than optimizing a log-likelihood function or computing the efficient score. Nonetheless, the control chart has also an inherent delay and must be calibrated carefully. Finally, a benefit of the likelihood approach is that the likelihood function is easily extended to the case of a space-time process. This should allow to implement a detector able to detect and locate quakes considering the entire global network.

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