EaST: Earth Seismic Tomographer

Building a network of volunteer smart mobile devices for seismic travel times Earth tomography

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***Abstract* — The recent diffusion of smart mobile devices deeply influences current technological landscapes also supported by a blooming market economy. New forms of users, interaction styles and ubiquitous paradigms are growing with this technological revolution. Connected mobile devices equipped with accelerometers represent, for geological Research, the opportunity to increase the information on several phenomena that are difficult to study because of the limited availability of observation data. Information provided from a cloud of mobile sensors, randomly localized on the territory, may contribute to extend the fixed nature and the very limited number of traditional Earth observation points. This paper describes the Earth Seismic Tomographer system, a mobile application that analyzes triaxial accelerometer data, aiming at collecting travel time information on earthquake events. The system relies on the voluntary participation of users that devote personal mobile resources to detect and provide seismic data to the central server. The Earth Seismic Tomographer adopts neural network classifiers to separate user movement from the seismic signal. The proposed system will increase the amount of information on seismic events enabling Earth scientists to study problems still undetermined with the currently available data.**

Keywords - Mobile Smart Devices, Earthquakes, Seismic Tomography, Accelerometer Sensing, Neural Networks.

I. INTRODUCTION

Technological market and progress are depicting novel scenarios in which users and applications exploit increased degrees of connectivity and ubiquity. In several field of parameter estimation [2], for example, it would be indispensible for researcher to exploit the increased amount of data provided by new mobile smart mobile devices.

Indeed, new generation mobile devices are, almost always, equipped with accelerometers, orienteer and camera and often are GPS localized or, at least, estimate their position by triangulating GSM cells or WiFi repeaters.

This paper presents the Earth Seismic Tomographer system (EaST), a mobile application that aims at providing geologists with a redundant amount of data on seismic events by recording ground acceleration data.

The problem of estimating physical parameters values from experimental data is a crucial matter in many geophysical investigations. In geophysical literature, this problem is denoted as model inversion and the goal is to combine information arising from physical theories and from experimental results, in order to infer some characteristics of given Earth properties. In general, theories are represented by a set of equations relating values of unknown properties to the physical parameters observed in the experiment.

In particular, *seismic tomography* [13] is a technique aiming at reconstructing the velocity structure ($s(r)$ in equation 1) of a body, given the measurement of travel times (T in equation 1) of waves that have propagated through that body.

$$T = \int_{r[s]} s(r) ds \quad \textbf{(1)}$$

In this expression, s is the slowness and is defined as the reciprocal of the velocity: s = 1/v. The slowness, used instead of the velocity, keeps the integrand linear respect to the quantity we aim at retrieving.

It would be tempting to conclude from (1) that the relation between the travel time and the slowness is linear. However, this is wrong because the integration in (1) is along the path on which the waves travel. The rays are curves of stationary travel time, and hence the ray location depends on the slowness as well.

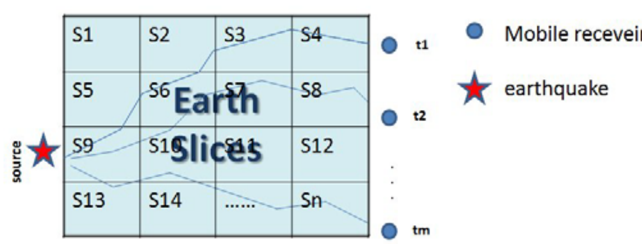

Figure 1. The discrete slowness model for seismic tomography.

Seismic tomography is thus a nonlinear inverse problem: the unknown slowness is present in (1) both in the travel time integral and in the integrand, where it determines the ray position $r[s]$.

When one divides the earth-model in cells where the slowness perturbation is assumed constant, the discrete form of (1) can be written as:

$$\delta T_i = \sum_j l_{ij} s_j \quad \textbf{(2)}$$

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In this expression, the subscript i labels the different travel times used in the inversion, while j is the cell index and l_{ij} is the length of ray i through cell j. Figure 1 depicts this discrete version with ray paths, homogeneous slowness cells, seismic source and receivers.

In the seismic tomography problem, the aim is to reconstruct, using (2), the Earth velocity model ($V_i=1/s_i$ for $i=1, \dots ,n$) from a set of travel time measurements. In the ideal case, an exact theory exists that prescribes how the data should be transformed in order to effectively reproduce the model. For some selected examples such a theory exists assuming that the required infinite and noise free data sets would be available.

Nevertheless, the model that we aim at determining is a continuous function of the space variables. This means that the model has infinitely many degrees of freedom while, in a realistic experiment, the amount of data that can be used for the determination of the model is usually finite. A simple count of variables shows that the available data do not carry sufficient information to determine uniquely the model. The fact that in realistic experiments a finite amount of data is available to reconstruct a model with infinitely many degrees of freedom necessarily means that the inverse problem is not unique in the sense that many models explain the data equally well. The model obtained from the inversion of the data is therefore not necessarily equal to the true model to seek.

EaST project aims at improving the availability of seismic data, providing more information about seismic events, about their effects on the territory and contributing to improve Earth phenomena models. In the case of a seismic event, a network of volunteer sensing devices sends toward the server the temporized acceleration tracks. The server offline elaborates these tracks to detect the seismic rays travel times providing a new amount of information for the Seismic tomography and other geophysical problems.

The remainder of the paper is organized as follows: Section II presents and discusses similar research approaches; Section III details the system, while Section IV concludes the work.

II. Related Work

This section resumes the state of the art related to seismic signals detections and the approaches aiming at automatically understanding user movements from accelerometer data.

The earthquake detection is the goal of the *Quake-Catcher Network* project [16]. It is a collaborative initiative for developing the world's largest, low-cost strong-motion seismic network. The QCN is collecting a great amount of data on seismology by combining new Micro-Electro-Mechanical Systems technology with volunteer seismic stations distributed computing. The system has a twofold nature since it utilizes two kinds of sources:

- laptop built in sensors (the authors refer that only Apple and ThinkPad laptops offer this feature),
- specific sensing components attached to internet-connected computers (that need to be bought and configured).

QCN originated from an idea of Elizabeth Cochran [3], a seismologist at UC Riverside. The project started in 2006, and is operative since April 2008, now being one of the largest and densest earthquakes monitoring system.

Actually, QCN is the only system similar to EaST in terms of expected diffusion and limited cost. Obviously, there are other specific Earth monitoring networks, but they are based on a small number of accurate but geographically concentrated observation points. Differently from Cochran et al., we completely rely on ordinary mobile devices and on already available hardware sensors to increase the amount of information on seismic events enabling Earth scientists to study problems still undetermined with the currently available data. Additionally, in our case, the adoption of mobile devices causes the perturbation of seismic data with user movements and it is necessary to adopt some detection mechanism.

The neural networks (NNs) are software classifiers inspired to biological nervous system [10]. NNs simulate the human brain activities with a self-adapting system composed of simple elements, the neurons, connected with each other and operating in parallel. The theory of NNs has a broad application sphere in several fields including pattern recognition, identification, classification, speech, vision, and control systems. The main interesting feature of NNs is in their self-adaptation mechanism that can solve problems that are difficult for conventional computing or human beings. As in nervous systems, the connections between elements determine the overall network function. The training phases of a network adapt it to the desired function by adjusting the values of the connections between neurons.

Earthquake detection and classification belong to a class of problems where artificial NNs may be useful [4].

Indeed, the most important characteristic of a NN is its capability to learn from examples, so that NNs are powerful tools in approaching problems, like the earthquake related class, that are difficultly described using a classic algorithmic strategy.

In [17], Romero proposed two NN applications at earthquake detection problem: a simple NN (Perceptron [18]) classifying earthquakes recorded at the Bardonecchia (North Italy), and an auto associative NN that has proved useful to build an adaptive neural trigger for earthquake detection.

Sharma et al. present and evaluate the precision of several approaches for detecting seismic event signals in presence of background noise [20]. In their work, the authors examine several trigger algorithms, ranging from a very simple amplitude threshold type, to sophisticated pattern recognition, adaptive methods and NN based approaches. All the detection triggers have been tested on natural events and on artificial ones (e.g., underground nuclear explosions).

In our case, we do not have previous knowledge about the sensitivity of devices and their response to seismic events, but we can exclude perturbations due known user movements. As a dual approach of previous ones, the

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adoption of NNs let us filter out, on the client device, a good number of false positive detections by training neural classifiers on typical user movements.

In [11], user activity classification is performed analyzing acceleration magnitude and rate of change, as well as piecewise correlating the three components of acceleration. A simple Multi-Layer Perceptron is trained for classification.

Fabian et al., train a set of NNs to recognize six typical human activities: resting, typing, gesticulating, walking, running and cycling [5]. They collect body-part acceleration values reading three MotionBand devices attached to the test subjects. In our case, we have a single accelerometer moving with the user, as in [22] where Yang et al. adopt a multilayer feed-forward NN as activity classifiers. They propose an effective activity recognition method using acceleration data collected from a single triaxial accelerometer.

III. THE PROPOSED SYSTEM

EaST is a client server system aiming at collecting travel time information on earthquake events. Each client is a mobile receiving station and sends seismic acceleration data to the central server. To prevent false positive seismic triggers due to user movement, several NNs, trained on typical user activities, detect perturbations that can interfere with the seismic detection. The configuration of clients is fully dynamic: the server stores all configuration data and provides updates to all clients. It is always possible to change the client behaviour simply acting on the server, an easy and user transparent operation compared to the distribution of a new release of the client. This runtime dynamic configuration is not limited to simple processing parameters but also to the architecture and the configuration of adopted NNs. As NN engine, EaST system embeds Joone [9]. The core engine of Joone is suitable for small devices, having a small footprint and is executable on Personal Java environments. The framework enables to serialize a NN object (structure and weights) to a file. On update, the server propagates new NNs to each client.

Actually, the client application is only available for Google's Android, an open source Linux based platform for mobile devices [1], but we foresee to develop EaST client versions for other mobile platforms. The Android architecture has been developed by the Open Handset Alliance [15], a federation of device manufacturers, mobile operators and other companies (i.e., semiconductors manufacturers, software developers, etc.). The Alliance ensures that the same implementation of the software is suitable for all devices that support the Android software stack. This feature greatly improves diffusion expectations of EaST system.

An interesting feature of Android is the availability of free API libraries for controlling the device hardware. The Android SDK includes APIs for location-based hardware (such as GPS), camera, network connections, Wi-Fi, Bluetooth, accelerometers, touch-screen, and power management [1].

Accurate location and time for each client are crucial for the effectiveness of measurements. At this aim, EaST clients interrogate the Android Location service searching for GPS localization that is affected by an error lower than 20 m. As an alternative, if GPS is not available (often in indoor locations) clients use the network localization, whose precision is of some hundreds of meters. In any case, the error esteemed for the localization is communicated to the server. In the case GPS service were available, the time provided by satellites is used also for periodically synchronizing the client clock. Alternately, the time is periodically synchronized with the Network Time Protocol time as in [3], with a verified a precision of 20 ms [6].

A. *The instrument and the phenomenon sensitivity*

To tune and test the system, we use mobile devices equipped with a Qualcomm processor working at 528 MHz, 512 MB ROM and 288 MB RAM, an internal GPS receiver, a G-sensor accelerometer, a digital compass, a 320x480 pixel touch-screen and an opposite 3.2 megapixel integrated camera. As additional memory, the devices support SD cards up to 16 GB. In particular, the devices have an AK8976A 3-axis accelerometer, even if the SDK ensures the application to be suitable for all Android devices that are equipped with a similar low cost hardware component.

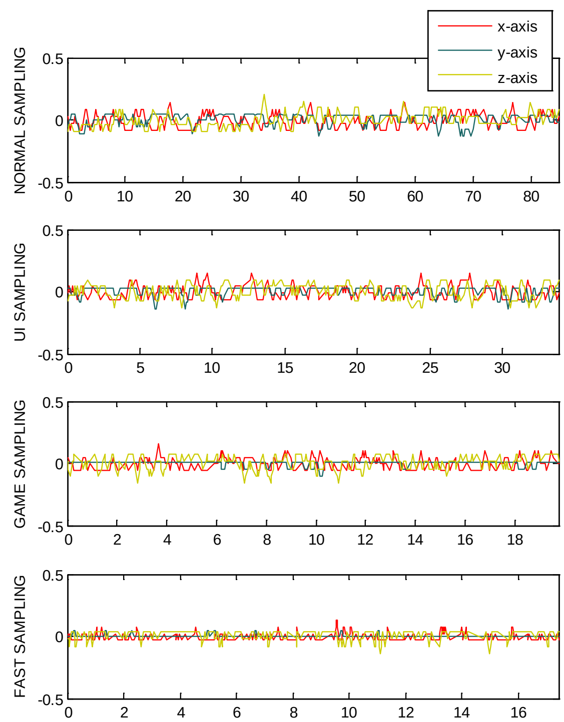

Figure 2. The noise affecting accelerometer for 300 measurements at different sampling rates, on a time scale in seconds.

The Android SDK lets programmers to choose between four sampling frequencies with a progressively decreasing sampling period: NORMAL, UI (i.e., User Interface suitable sampling rate), GAME and FASTEST. It is important to point out that Android system is a multitasking one and, therefore, the sampling frequency is not constant.

The coordinate space adopted for acceleration sensing is the OpenGL ES [14] coordinate system. When the phone lies

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on a table with upward screen, the origin is in the lower-left corner with respect to the screen, with the X axis horizontal and pointing right, the Y axis vertical and pointing up and the Z axis pointing outside the front face of the screen. In this system, coordinates behind the screen are characterized by negative Z values. The axes are not swapped when the device's screen orientation changes.

All values are expressed in *IS* units (m/s^2) and measure the acceleration applied to the phone minus the force of gravity.

If the device lies flat on a table, the force of gravity acts only on the z component of the sensed acceleration. When the device is in a jacket pocket of a user, like in reported samples, the acceleration component A_y is decreased with the force of gravity (- 9.81 m/s^2). The A_x and A_z components measure, respectively, a lateral acceleration and a front rear acceleration respect to the user.

Before starting the development of the system, we sampled the sensor noise and sensitivity at different rates. The objective of the feasibility study was twofold: verifying if earthquakes propagation time enables to obtain meaningful measures from devices spread on the territory and that the phenomena are perceptible in a geographic area wide enough respect to the temporal resolution of measures.

Figure 2 plots the accelerometer values, when the phone is in state of rest, sampled at all the available frequencies. In particular, 300 measurements are represented respect to time in seconds, and increasing frequencies are compared. The g_z component of the force of gravity has been subtracted from the A_z measure for better graphically comparing all the components on a smaller scale. By observing Figure 2, it is possible to note that the FAST SAMPLING subplot appears as the less affected by measurement noise. For this reason, and to obtain the best signal resolution possible, we adopted the fastest frequency available for sampling the acceleration. Even in the fastest sampling case, produced track files are thin respect to modern microSD cards and network transmission rates: 1.70 Mbytes are sufficient to record more than 15 minutes of signal and can be compressed in less than 300 Kbytes. As depicted, the error results lower than 0.2 m/s^2 $= 2\%g$. These values enable to detect a seismic signal from a wide geographic area surrounding the source.

TABLE I. A SAMPLE OF PEAK GROUND ACCELERATIONS FOR SEISMIC EVENTS

ACCELERATION (%g)					
SOURCE	**M**	**Depth Km**	**10 Km**	**50 Km**	**100 Km**
1	5.0	10	6	1	//
2	6.0	57	20	5	//
3	6.2	60	2.1	1.0	0.5
4	6.8	40	9	4-7	1
5	6.2	10	20	7	3
6	6.8	35	30	10	4
7	6.9	11	40	10	//

Table I resumes the peak ground acceleration measured during some strong seismic events and obtained analyzing the USGS (U.S. Geological Survey) maps [19]. The reported measures of peak ground acceleration are expressed as a percentage of g (gravity acceleration).

Comparing a sample of seismic ground acceleration values (Table I) with current instrument sensitivity, it is possible to esteem that the devices will be capable to detect arrival times for seismic events in a range of 10-50 Km from the source. However, it is important to point out that this estimation is pessimistic, since the ground acceleration is the minimal measured since does not consider the amplifying effect due to building structures and heights.

Table II reports the earthquake transmission velocities of some soils. The values ensure a time delay of several seconds, compatible with the time resolution of the instrument, in a distance of 50 Km, esteemed according to Table I, to be the sensitivity of EaST clients.

TABLE II. EARTHQUAKE TRANSMISSION VELOCITIES, V_P, AGGREGATED BY SOIL CLASSIFICATION

SOILS	
Classes	**V_p (Km/s)**
Rocks	5.7 - 0.85
Dense Clays	1.4 - 0.5
Sands and Gravels	0.7 - 0.1
Loose Clays	0.16 - 0.14

extracted from [21]

B. The detection

The EaST system is based on a mobile and not inertial sensor device set. The localization of sensor is performed via GPS, that provides also time synchronization, or by network triangulations, even if the detection algorithm has still to cope with all the problems due to the user movements.

The detection of a seismic event is performed both on the clients, to avoid overloading the server with false positives, and on the server, where a predetermined fraction of seismic triggers is always sent.

On the client, the detection is based on three subsequent phases characterized by increasing computational complexity and based on the dynamically updated execution parameters α, β, γ:

- *STA/LTA detection*: evaluation of *Short Time Average* (STA) and *Long Time Average* (LTA) ratio,
- *probabilistic positivity*,
- *detection of user activity*.

In particular, α ($\alpha>1$) represents the threshold for STA/LTA detection, β ($0\leq\beta\leq1$) the probability of excluding the NN detection of user activity and γ ($0\leq\gamma\leq1$) the NN sensitivity.

The clients continuously perform the *STA/LTA detection*: they observe a time window of accelerometer signals and compare the relative average values LTA with a shortest sample average value, the STA. When the STA/LTA ratio exceeds α, the client is measuring a rapid change in acceleration signals and an earthquake event is possible.

Probabilistic positivity is the second phase of the algorithm and guarantees that, after *STA/LTA detection*, a known percentage of the receivers will however send the seismic trigger to the server. This phase enables to avoid starting the next one, and to demand a part of the detection to the server. The server maintains a list of working devices positions, and in presence of a good coverage of suspected area, is able to understand when a seismic trigger is a false positive to discard, according to the diffusion of the alert. Exploiting this server capability, during the *probabilistic positivity* phase, we explicitly exclude with p=γ, the NNs detection; basing on the other near clients, the server understands if the signalled variation in the ratio STA/LTA is due to a seismic phenomenon.

As stated in [20], STA/LTA based detection usually does not perform well at sites with high, irregular and in particular, man caused acceleration noise.

To overcome this limitation, the proposed algorithm combines this approach with the NN analysis of user activities, the *detection of user activity* phase. This enables to obtain good client robustness to user movements, still requiring only a light computation for on-line controlling the accelerometer signals.

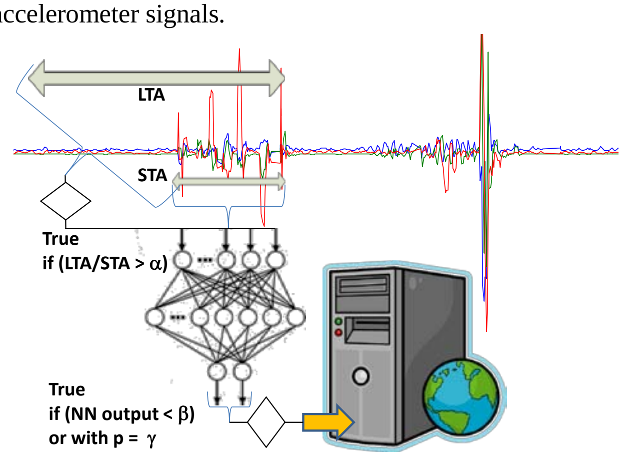

Figure 3. A schematic view of the seismic detection algorithm

As previously stated, the adopted sampling frequency for the sensor is the highest available, and oscillates around 15 measures per second (since Android is a multitasking system, the frequency adjusts according to the system scheduler). This big amount of on-line accelerometer data and the voluntary nature of user participation in the project, impose a strong optimization of required device resources.

Indeed, the evaluation of user activity is the only expensive phase, in terms of required processing time, as four NNs classify the acceleration signal aiming at excluding false positives seismic triggers. This phase is executed only when the STA/LTA ratio exceeds the threshold α and with p= 1-γ.

Figure 3 depicts the detection algorithm, graphically representing the acceleration and the samples adopted for LTA e STA. The execution parameters α, β, γ and the structure and configuration of the NNs are updated on the client during the time synchronization, when necessary.

Further details on the adopted NNs and the training phases are reported in next subsection.

Resuming, when the ratio STA/LTA exceeds α, with p=γ or when the NNs do not recognize any known user movement pattern (NNs output < β), a text file is prepared and sent to the server, communicating the client position, the device orientation, the current time and the acceleration data.

C. *NNs and training*

The NNs are software classifiers inspired to human brain [10]. NNs simulate the human nervous system activities with a self-adapting system composed of simple elements, the neurons. Each neuron computes a simple threshold function on its inputs. NNs are usually constructed organizing neurons in three layers: input layer, hidden layer and output layer.

According to [17] and [11], the EaST clients embed four simple Back Propagation NNs aiming at recognizing user movements as walking, using a lift, climbing the stairs or moving in a vehicle.

The Back-Propagation BP NNs are trained in a two steps procedure:

- in the first step, the forward propagation by positive model, the NN analyzes a sample and calculates, layer by layer, the input and output,
- in the second step, the error respect to the expected classification is propagated back and proportionally adjusts the weight and neuron threshold.

The operation is repeated until the error reaches the allowable range. The recognizing of user movements is not a simple task, and the variability in user habits does not help to give specific analytic functions or descriptions.

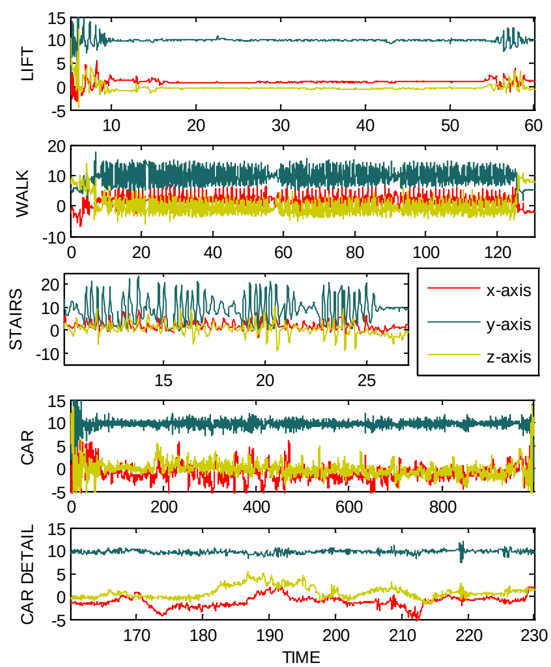

Figure 4. Acceleration sampled during four typical user actions.

In this way, the NNs can learn from historical data, stimulate the movement through neurons network, and approach the practical function by hidden layers to establish a relation model between acceleration and user movements, without considering specific details. Figure 4 reports one graph for each class of samples on which we trained the first version of EaST clients. The training phase is still on going to obtain a good generalization of NNs to different users. More NNs, trained on other typical user movement patterns, are also going to be prepared form embedding on the EaST client.

During the detection algorithm, when the neural detection is required, the acceleration data are analyzed by the NNs. If the NNs do not classify any known user movement pattern, the client position and the device orientation, the current time and the acceleration data are sent to the server.

IV. CONCLUSION

The EaST system is still in tuning: we are simulating a device population to establish the best values of execution parameters respect to client number and geographical density. Once distributed, the EaST system will be based on the voluntary contribute of users that are asked to offer some resources on their mobile devices to detect seismic waves and provide seismic data to the central server. It is the analogous of other volunteer computing projects such as SETI@home (radio telescope data), Einstein@home (gravitational wave data), and climateprediction.net (testing the accuracy of climate models) that exploit user desktop PC resources to perform heavy scientific computations. In our case, the aim is slightly different since we aim at collecting data and do not require, usually, computational resources to our users.

After the current tuning of the system, the adoption of Android will let us freely distribute EaST application and arrive to a big community of potential users just using the official distribution channel of this platform: the Market. Android has surged to fourth place overall, growing from 1.6% to 9.6% market share from 2009 to 2010 [8].

The future development of clients for other common mobile platforms will ensure a bigger diffusion of the EaST system and an increased amount of data available on seismic events.

Indeed, actual estimations of mobile technology future strongly encourage our and general interest toward these technologies. According to Gartner Inc., an information technology research and advisory company, location based services user number will grow from 96 million in 2009 to more than 526 million in 2012 [7] and the 3G connection will be available on the 61% of mobile devices [12]. In the foreseen landscape, it will be crucial experimenting and proposing new ubiquitous and distributed, often pervasive, applications exploiting available resources.

Besides its interest for Earth scientists, we also expect that the research work connected with the realization and the improvement of the EaST system, will provide also interesting results in human computer interaction field. A better understanding of user habits and movement patterns will improve and propose new forms of life logging, context based services and content providing.

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