AN INVERSE SENSOR MODEL FOR EARTHQUAKE DETECTION USING MOBILE DEVICES

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Abstract: We describe a sensory framework to be used for the purposes of earthquake detection using minimal cost, accelerometer equipped, hardware units. Combining techniques from mobile robotics this model is intended to address the current issue in the field whereby high fidelity hardware units tuned to detect specific characteristics such as wave features and/or high fidelity event models derived from data analysis are required for such detection. In this paper we present and contextualise the architecture under construction in addition to outlining the salient elements of the problem we are addressing.

1 INTRODUCTION

At the onset of an earthquake, dedicated detection systems are capable of issuing alerts thereby providing valuable time for people further from the event epicentre to take action to protect themselves. This is possible as the means employed to facilitate the transmission of alert information is generally faster than the speed of seismic waves. However this capability obviously relies on the existence of a monitoring network. Within the field of earthquake engineering two broad approaches have emerged toward the creation of such networks. One approach consists of creating banks of accurate units capable of detecting seismic characteristics because they have been tuned to detect specific characteristics such as fluctuating ambient seismic noise level. Countries such as Japan have successfully developed early warning systems based on such techniques. Unfortunately it is not always possible to deploy such technology in earthquake prone areas around the world for varying degrees of political, technical and financial considerations. Where such situations manifest themselves the use of commodity hardware as the foundation of a seismic detection network is a viable alternative. This highlights the second domain approach which consists of employing the distributed computing paradigm where the individual physical nodes are typically Laptop or Desktop computers equipped with sensors such as accelerators. For example the Network for Earthquake Engineering Simulation Cyberinfrastructure Centre (NEESit) has utilised the accelerometers in Apple Macintosh laptops to develop an educational and research platform for measurement and recording of vibrations and dynamic responses. Likewise the Quake-Catcher Network (QCN)2 links existing laptop and desktop computers with the aim of forming a large earthquake monitoring system.

While the availability of Laptop/Desktop based systems does remove a number of obstacles barring the realisation of detection systems the installations in themselves suffer from a number of manifest problems. For example the existence of networking infrastructure capable of linking the individual machines, the potential availability of technically skilled people (or appropriate training programmes) to operate the machines, the ability to quickly disseminate alerts is a required component of any such system.

Our aim is to directly address this problem by supplementing traditional Laptop/Desktop based approaches using mobile phone technology. The core design goal is to develop a portable system which is capable of running on constrained and resource limited hardware thereby allowing earthquake detection in sparsely seismically-instrumented regions. Therefore a key facet of the system is the development of a signal processing model which does not have the distributed quantitative analysis requirements of the Laptop/Desktop techniques mentioned above and is capable of operation in the context of low entropy sensory information. In this paper we present such a model, illustrating its core features and operational characteristics, and presenting initial results illustrating the competencies of the model and finally highlight areas

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of future work.

2 SEISMIC EVENT SIGNAL DETECTION/HANDLING

There are two broad approaches to the detection and/or handling of seismic event signals. One approach consists of creating dedicated accurate sensory units tuned to detect specific signal characteristics therefore making the units capable of detecting emergent seismic characteristics e.g. fluctuating ambient seismic noise level. The other approach consists of employing knowledge based reasoning and established signal processing techniques to derive signal processing techniques formed from the feature analysis of historical data.

Hardware based detectors use signal averaging techniques in an attempt to achieve an optimum signal to noise ratio which is capable of determining a true seismic event from a false positive. The ability of such sensors is directly related to the noise model that has been pre-determined and incorporated into the units. Such noise models are generally formed through traditional signal manipulation techniques i.e. the statistical analysis of an appropriate domain characteristic function. However to be useful in a practical sense this noise model must be determined for every new installation of such the units and limits the detection threshold thereby reducing the overall effectiveness of such units (Newmark and Rosenblueth,).

The direct application of Machine Learning and/or statistical techniques, typically realised in software, in the form of knowledge-based reasoning is an alternate approach which provides for a level of flexibility in the detecting of seismic activities. Such systems are exemplified in (Hewitt, 1992; Zareian and Krawinkler, 2009). In this case the detection threshold associated with the system is not directly dependent on a physical characteristic such as seismic noise level. Rather relevant characteristics are determined through the analysis of domain expertise in the form of historical data and knowledge acquired from human experts. The Laptop/Desktop based systems outlined previously typically employ such techniques. The gathered information is employed to construct an operational model which is used to evaluate the sensory information received from the Laptop/Desktop sensor(s). The overall success of such approaches however is largely dependent on characteristics such as the selection of appropriate domain classifications and refinement/training of the derived model.

Within the context of the domain we are addressing the realisation of an efficient and expressive signal processing mechanism is paramount to the overall performance of detection system. Unfortunately neither of the existing techniques outlined above are directly usable for what we need to achieve. Techniques associated with tuned hardware units are not usable because the hardware units we are concerned with are standard mobile phone handsets meaning that the modification of same would require specific technical expertise and the availability of specialised hardware which is not a feasible goal for the intended deployment locations. In addition the application of existing 'knowledge based' techniques is not directly possible because of the data requirements both in terms of constructing an initial model and subsequent data propagation throughout the network.

From an operational perspective, any signal processing technique must consider real time operation as being paramount. In addition there should be no requirement for historical knowledge. However any such information, if available, should be easily incorporated into the model developed using the processing technique. Finally the technique must accommodate low entropy sensory information.

In evaluating these requirements techniques from a number of varied domains such as speech recognition e.g. (Vargas et al., 2001), and telecoms e.g. (Murooka et al., 2001) and mobile robotics e.g. (Ehlers et al.,) were considered. After domain evaluation we determined that the problem that is closest to the problem we are addressing in developing our signal handling model is the field of Occupancy Grid based robotic mapping.

3 MOBILE ROBOTIC MAPPING

Within the field of mobile robotics a key concern is providing the robot with the ability to acquire a model of its operating environment as this model is required for the safe and productive operation of the robot. The actual performance of the robot in acquiring a meaningful spatial model of its operating environment depends greatly on its capability to quickly evaluate the potentially erroneous information received from its sensors. As it operates in the environment, the robot gathers sensory information and subsequently incorporates this into a representation of the environment. Occupancy Grids have become the dominant paradigm for environmental modelling in mobile robotics because of their operational characteristics (Kortenkamp et al., 1998) . The creation of these Occupancy Grid maps is a non trivial process as the robot has to interpret the findings of its sensors in order to make deductions regarding the state of its environment. This is facilitated by the use of a sensor model which is a means of interpreting received signals through perceptual channels. In occupancy grid based robotic mapping there are largely two types of sensory model; the Inverse Model and the Forward Model(Collins et al., 2007). In the context of our requirements the inverse approach is currently most applicable. This is because it facilitates iterative real time operation without any requirement for historical knowledge and facilitates operation with low entropy sensory information.

4 PHYSICAL ARCHITECTURE

A key design goal is to produce a portable system which is able to run on constrained hardware. Although the target device for the prototype is a mobile phone it is envisaged that the software could run on other more limited embedded devices. The overall design of the prototype can be split into specific problem domains involving obtaining the data, communication of the data, encoding of the data and processing of the data on the device itself.

4.1 Obtaining the Data

While movement will be detected by the accelerometers contained within the device, an initial decision is how often to sample this movement and how many samples are needed before we process the data. Once we have accumulated sufficient samples this data needs to be analysed to decide whether or not we think an adequate amount of shaking or movement is taking place. Studies of accelerometer data include calculating and using the covariance of the values obtained (Ravi et al., 2005). For the prototype currently in development we take the covariance of our X, Y sample data using equation 1.

$$covar = (1/(n-1))\sum_{i=1}^{n}(x_i - \hat{x})(y_i - \hat{y}) \qquad (1)$$

We then compare this *covar* result with a predetermined threshold value. If it exceeds this threshold we must then communicate our findings to other clients.

4.2 Communicating the Data

The first challenge to overcome is deciding how to broadcast or share data between multiple connected devices in a scalable way. The Spread Toolkit offers an open source solution based on a shared message bus. It has been optimised to provide efficient message exchange with the ability to guarantee delivery

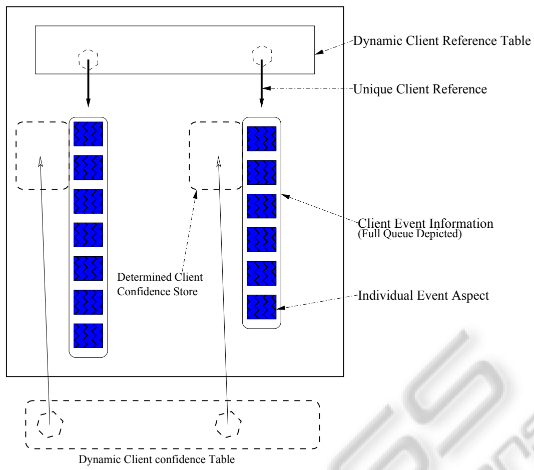

Figure 1: Device architecture.

and ordering of messages if required. To improve performance we will use unreliable communication. Each mobile client connects to an individual Spread daemon using a uniquely generated id. In addition, Spread daemons can be connected together to form a larger shared single communication bus where Spread daemon 1 connects to Spread daemon n.

4.3 Processing the Data on the Device

All messages received by a single client will be queued for a specific period of time. Thus, the number of independent queues created reflects the number of unique clients who have transmitted messages within the sampling time period. Processing the queues involves examining the number of queues at time t as well examining their queue length. If the number of queues is below a certain threshold or the mean queue length is below a certain threshold we can reset all queues and wait for the next sampling period before repeating the process. Otherwise, we need to process the data in the queues. For the prototype each queue contains data representing a covariance value v obtained from the accelerometer data. Each queue will have an independent scalar value representing a confidence level k. Applying $k(v_1, v_2, \ldots, v_n)$ yields $(kv_1, kv_2, \ldots, kv_n)$ for each queue. Summation of these queue vectors will provide a simplistic overview of whether or not we suspect an earthquake is taking place. Each time the queues are processed they are cleared ready for the next sample. A key challenge will be deriving an accurate confidence scalar value for each queue. This will ultimately need to take into account historical data between sampling cycles.

All software used or written needs to be portable and able to run on ARM and MIPS based hardware. The software must also operate within the constraints of the target device. The hardware used for the prototype is the Openmoko Freerunner[1]. Significant features of the device include its accelerometers, WiFi and GPRS. The ability to test over a GPRS connection will be important as it may not be possible to access a wireless access point or there may not be a 3G network available. Therefore being able to concisely encode data for communication across Spread will be essential. Regardless of the connection we also want network communication to be light-weight in terms of processing load. This eliminates standard approaches such as structuring packets with XML data (Moore, 2007).

5 SEISMIC DETECTION MODEL

From an operational perspective the architecture we are in the process of realising operates as follows. Each device begins an operational cycle by populating its client event queue through taking in data propagated from the various other devices in the network. This per queue information must then be used as the basis for determining the whether or not an event may be happening. This problem is far from trivial as each queue is subject to a potentially different and non deterministic sampling rate meaning that it is the indirect information contained within the queues that must be used. In addition each device will have an independent view of the problem meaning that it is not possible to directly rely on device interdependency characteristics.

5.1 Client Queue Information

As a device can only determine information about the operating environment indirectly through its sensor(s) and the information propagated from its peer units the determination of a world model is an applied example of an estimation theory problem (Thrun, 2002). Therefore to facilitate the interpretation of the data provided from a client event a probabilistic sensor model of the form $p(r|z)$ is used. This model facilitates the derivation of the individual client event confidence values v, mentioned previously in section 4. Therefore:

$$v_i = p(r_i|z_i)$$

where the model we use in this prototype is based upon the characteristics outlined previously in section 4.3. This model relates the client event reading r to the true event state z. This density function is subsequently used in a Bayesian estimation procedure to determine the event state probabilities. Finally a deterministic world model is employed to facilitate the derivation of a optimal world estimator which can be propagated between the individual units that form the world state.

A classical Bayesian approach is used for the determination of the per queue confidence score. Given the current estimate of the state of client C_i, $p[s(C_i) = SE|\{r\}_t]$ based on the observations $r_i = r_1, \ldots, r_t$ and given a new client observation r_{t+1} the new state estimate is provided by

$$k = p[s(C_i) = SE|\{r\}_t + 1] = \tag{2}$$

$$\frac{p[r_{t+1}|S(C_i) = SE]p[S(C_i) = SE|\{r\}_t]}{\sum_{s(C_i)} p[r_{t+1}|s(C_i)]p[s(C_i)|\{r\}_t]}$$

In the above the previous estimated value of the client state $p[S(C_i) = SE|\{r\}_t]$ serves as the prior and is obtained directly from a localised representation of the global state. The new state of a particular client. determined through the above, is subsequently stored in this representation and propagated to the world.

To facilitate prior estimation for client state a simplified one dimensional Gaussian estimator model is employed.

$$p(r|z) = \frac{1}{\sqrt{2\pi\sigma}} exp\left(\frac{-(r-z)^2}{2\sigma^2}\right) \tag{3}$$

5.2 Inter Device Confidence Regions

As presented above the sensor model is a one dimensional construct associated with a determined or evaluated distance between client devices. Therefore the model can be considered a client information axis from the one dimensional viewpoint. While useful for determining information relating to the 1-1 spatial mapping directly between the devices the model cannot consider areas outside of this conceptual spatial line. It is conceivable that the spatial area between a host device and its client will is also an area of interest. In particular it would be beneficial to have the ability to model a region of confidence emanating directly from the host device to the immediate vicinity of the client device.The basic premise of this concept is outlined in figure 2. When extended in this manner the probabilistic model approaches more closely the type of robotic mapping inverse sensor model highlighted previously. The extended model can be specified as equation 4 where Q is the angle associated with the created confidence region.

$$p(r|z,Q) = \frac{1}{2\pi\sigma_r\sigma_Q} exp\left[-\frac{1}{2}\left(\frac{(r-z)^2}{2\sigma_r{}^2} + \frac{Q^2}{\sigma_Q^2}\right)\right] \tag{4}$$

[1] http://openmoko.com

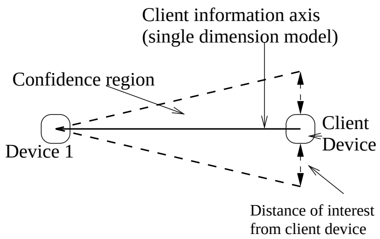

Figure 2: Creating a confidence region between devices.

The availability of these inter device confidence regions will provide for a more information rich profile of the event to be computed. In addition the overlapping of such regions will provide for the ability of assessing and verifying the information coming from individual clients thus adding a novel dimension to the client confidence estimation.

6 MODEL CONSIDERATIONS

As the architecture evolves the consideration of sensory units or other sources of relevant information is necessary. These considerations are highlighted here.

6.1 Client Event Information

At its core the actual sensor model is a statistical estimation formulation which interprets relative range information received from peer devices. Upon the activation of a devices sensors an event signal is propagated through the network. The determination of realistic events on a device versus false positives or false negatives is a separate problem to the data signal handling the sensor model is designed to consume and hence an exposition of same is outside the scope of this context. When an event signal is received the sensor model calculates a probabilistic profile for the event. To illustrate, consider the ideal scenario where a device receives notification of an event from a peer device at what is determined to be at distances of 60km and 100 km respectively from the device. The associated probabilistic profiles determined through the model are outlined in figure 3 where it can be seen that the model is Gaussian in nature. In terms of the device architecture each profile corresponds to a single component of an event queue. The preceding example presented the model in the ideal scenario of there being a 1-1 correspondence between the physical devices distance and the actual distance the information has been determined to travel. In real world settings such an assumption cannot be guaranteed. The model takes cognisance of this fact by its nature as illustrated in figure 4.

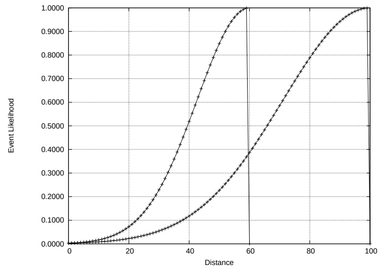

Figure 3: Event profiles for hypothetical distances of 60km and 100km respectively.

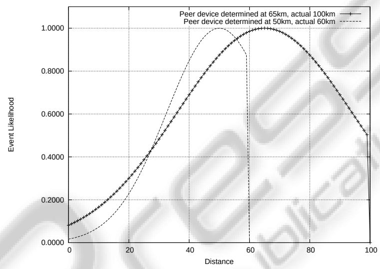

Figure 4: Event profiles in the context of non ideal peer device distances. Hypothetical actual distances are 50km and 65km respectively.

6.2 Information Source Integration

To increase the capability of any such system in general requires that multiple sources of information can be incorporated into a single, useful, information source. This is known as the data fusion problem. Fusion processes are frequently categorised as low, intermediate or high, depending on the processing stage at which fusion takes place(Klien,). Low level fusion, (Data fusion) combines several sources of raw data to produce new raw data. The expectation is that fused data is more informative and synthetic than the original inputs. Within the context of multi-device seismic detection this integration can be performed using a formulation such as that outlined in equation 3 to combine the estimates provided by the independent clients. For two clients C_1 and C_2 this means using the associated client data models $p_1(r|z)$ and $p_2(r|z)$ as the basis for determining the associated combined probability and subsequently applying an appropriate normalisation across the state encapsulated in the client confidence table illustrated in figure 1.

7 CONCLUSIONS AND FUTURE WORK

In this paper we have detailed a sensor modelling framework for earthquake detection using mobile devices which is used within the context of a novel seismic event detection architecture. The sensor model outlined is a probabilistic one Gaussian in nature and similar to the inverse sensor models prevalent in the robotic mapping field. As such it is capable of incrementally and efficiently interpreting event signals propagated throughout the network without the need for predetermined models or sensor associated segmentation decisions. For example the characterisation highlighted in section 6 illustrated that meaningful client event evaluation is possible with a minimal of information i.e. an event notification and a client distance estimate.

In terms of future work regarding the model and its usage a number of areas are prevalent. The choice of an inverse sensor model has some specific implications. Because of its theoretical basis the disambiguation and analysis of client event data is achieved primarily through the use of additional sensing. This has performance implications which need to be addressed. Another area of future work is determining appropriate characteristics for the extension of the one dimensional sensor model to two dimensions. The attribute of interest here is determining a meaningful distance of interest from a client device. To address this problem we initially propose to employ simple heuristic values determined from operational experience. Our long term aim however, is to facilitate the automated derivation of the distance of interest, using triangulation between clients. The evaluation of received client events to determine the true likelihood of an actual earthquake event as opposed to user directed movement is another area of future research. Benchmarking the detection ability of our technique and subsequent model refinement is also an obvious area of future work. Toward this end we intend to correlate our detection results with actual real earthquake data obtained from national earthquake centres and the Stanford Quake-Catcher Network. Finally within the context of the project as a whole another important area of future work will be the specification of a meaningful benchmarking technique, applicable to the domain, to facilitate direct quantitative comparison between techniques such as ours and natural language centric techniques such as the U.S. Geological Surveys Twitter Earthquake Detector (TED)[2].

REFERENCES

Collins, T., Collins, J., and Ryan, C. (2007). Occupancy grid mapping: An empirical evaluation. In *Proceedings of Mediterranean Conference on Control and Automation*.

Ehlers, F., Gustafsson, F., and Spaan, M. Signal processing advances in robots and autonomy. *EURASIP J. Adv. Signal Process*, 2009.

Hewitt, C. (1992). Open information systems semantics for distributed artificial intelligence. *Foundations of artificial intelligence Special Issue of 'Artificial Intelligence' Series*, pages 79–106.

Klien, L. *Sensor and data fusion: A tool for information assessment and decision making*. SPIE Press.

Kortenkamp, D., Bonasso, R., and Murphy, R. (1998). AI-based Mobile Robots: Case studies of successful robot systems.

Moore, J. P. T. (2007). Thumbtribes: Low bandwidth, location-aware communication. In Obaidat, M. S., Lecha, V. P., and Caldeirinha, R. F. S., editors, *WINSYS*, pages 197–202. INSTICC Press.

Murooka, T., Takahara, A., and Miyazaki, T. (2001). A novel network node architecture for high performance and function flexibility. In *ASP-DAC*, pages 551–557.

Newmark, N. and Rosenblueth, E. *Fundamentals of earthquake engineering*. Prentice-Hall.

Ravi, N., Dandekar, N., Mysore, P., and Littman, M. L. (2005). Activity recognition from accelerometer data. In *IAAI'05: Proceedings of the 17th conference on Innovative applications of artificial intelligence*, pages 1541–1546. AAAI Press.

Thrun, S. (2002). Robotic mapping: A survey. In Lakemeyer, G. and Nebel, B., editors, *Exploring Artificial Intelligence in the New Millenium*. Morgan Kaufmann.

Vargas, F., Fagundes, R. D., and D. Barros, J. (2001). Summarizing a new approach to design speech recognition systems: A reliable noise-immune hw-sw version. *Integrated Circuit Design and System Design, Symposium on*, 0:0109.

Zareian, F. and Krawinkler, H. (2009). Simplified performance based earthquake engineering. Technical report, Stanford University.

[2] http://recovery.doi.gov/press/us-geological-survey-twitter-earthquake-detector-t ed/