2012 International Conference on System Engineering and Modeling (ICSEM 2012)
IPCSIT vol. 34 (2012) © (2012) IACSIT Press, Singapore

Using Time Series Analysis to Enhance Tele-Monitoring of Building Sensor Data

Apkar Salatian [1, a], Francis Adepoju [1, b], Bruce Taylor [2, c]

[1] School of Information Technology and Communications, American University of Nigeria, Yola Bypass, PMB 2250, Yola, Nigeria

[2] Scott Sutherland School, the Robert Gordon University, Garthdee Road, Aberdeen AB10 7QB, United Kingdom

[a]apkar.salatian@aun.edu.ng, [b] francis.adepoju@aun.edu.ng, [c] b.taylor@rgu.ac.uk

Abstract. Building tele-monitoring can be considered as the transmission of large volumes of continuous and noisy environmental data generated by the environmental sensors in buildings from one site to another using computer and telecommunication technology for purpose of remote building management. A common medium for building tele-monitoring is broadband which presents 2 major challenges in developing countries: the demand for bandwidth can easily outstrip the revenue realizable that is needed to pay for the network infrastructure investment so lower (cheaper and slower) bandwidth is normal; a consequence of restricted bandwidth on access pipes is service contention at the customer site, even if core bandwidth exists to deliver the services. In this paper we propose a time series analysis technique called data wavelets to perform data compression to address the challenges of broadband for data transmission in developing countries.

Keywords: Tele-Monitoring, Facilities Management, Building, Data Compression, Wavelets.

1. Introduction

Increasingly companies (supermarkets, hotel and leisure chains), with large portfolios of properties will centralise the facilities management of these geographical spread out buildings and sites either within their own organisation or outsource it to specialist facilities management companies. This will require everything to be connected across the internet: security cameras, Heating, Ventilating, and Air Conditioning (HVAC), lifts, lighting, energy, water, waste, IT, Communications, fire safety. Cisco's security and facility operations centre in Bangalore is one of five around the world that provides centralised management of security, energy, utilities, building facilities and transportation around the world for Cisco's offices and 60,000 employees [1]. Likewise, many other IT and engineering companies (IBM, Microsoft, Siemens, GE) are also implementing smart and sustainable communities.

City planners in south China have laid out an ambitious plan to merge together the nine cities that lie around the Pearl River Delta [2]. The new mega-city will cover a large part of China's manufacturing heartland, stretching from Guangzhou to Shenzhen and including Foshan, Dongguan, Zhongshan, Zhuhai, Jiangmen, Huizhou and Zhaoqing. Together, they account for nearly a tenth of the Chinese economy. Over the next six years, around 150 major infrastructure projects will mesh the transport, energy, water and telecommunications networks of these nine cities together, at a cost of some £190 billion. Creating mega-regions such as these and interconnecting them around the globe will become the norm as the world population grows from 6bn to 9bn by 2050. These mega-regions will in operation consume resources (energy, water, food) and generate waste on unprecedented scale. One way of making urban living on this massive scale sustainable is to create smart and sustainable communities. Other smart cities or regions include Masdar City in Abu Dhabi, Singapore, PlanIT Valley in the municipality of Paredes outside Porto, Portugal. The Intelligent Community Forum in January named its Top Seven Intelligent Communities for

2011: Chattanooga, Tennessee; Dublin, Ohio; Eindhoven, Netherlands; Issy-les-Moulineaux, France; Riverside, California; Stratford, Ontario; Windsor-Essex, Ontario.

Poor developing countries may wish to skip the industrialization stage of development and aim to go straight to a low carbon international service based economy. Wireless communications and local sources of renewable power make it feasible for these countries to leap-frog the installation of an expensive nationwide utility infrastructure to create communities that are wirelessly connected together and the rest of the world.

Smart connected communities will generate considerable amounts of data that will require to be analysed and acted upon in real time. This tele-monitoring of building data will allow remote management of buildings for more efficient and cost effective operation of the building estate. Tele-monitoring can be considered as the transmission of large volumes of continuous and noisy environmental data generated by the environmental sensors in buildings from one site to another using computer and telecommunication technology for purpose of remote building management.

One of the media for facilities management and smart communities to perform tele-monitoring is broadband, which, in turn, presents further challenges in developing countries which need to be addressed. The problem of broadband in developing countries is the lack of telecommunication infrastructure which is mainly due to the capital cost for such telecommunication infrastructure deployment and operating or running cost. Consequently, bandwidth demand can easily outstrip the revenue realizable that is needed to pay for the network infrastructure investment. As a result, developing countries generally have lower bandwidth than urban areas – this makes data transfer slow. Moreover, when operating in a rural multi-service environment a consequence of restricted bandwidth on access pipes is service contention at the customer site, even if core bandwidth exists to deliver the services – this can arise if there are a number of devices at the site that can request services with aggregate bandwidth greater than can be delivered over the access connection [3]. One approach to deal with low bandwidth and service contention at a rural site is to use data compression because it will make better use of bandwidth since smaller files take up less room on the access pipe and are therefore faster to transfer over a network.

In this paper we propose data wavelets as a lossy data compression technique to provide qualitative measurements in the form of trends from the high volume, high frequency and noisy data generated by the sensors in a building. Wavelets are a time series analysis technique that can be used for data compression from many different kinds of data, including high frequency noisy building sensor data. Sets of wavelets are generally needed to analyze data fully. A set of *complementary* wavelets will deconstruct data without gaps or overlap so that the deconstruction process is mathematically reversible – this is useful for our tele-monitoring application because the receiver of the compressed data can perform decompression to obtain the original signal.

2. The Algorithm

Wavelet algorithms divide a given function or continuous-time signal into different scale components which play a special role in wavelet analysis. Each scale component can be assigned a frequency range so it can then be studied with a resolution that matches its scale. If we look at a signal with a small window, we would notice small features. By contrast, if we look at a signal with a large window, we would notice gross features. The scaling function is therefore responsible for improving the coverage of the wavelet spectrum.

Generally, Wavelet transform of signal f using wavelet Ψ is given by:

$$W_{\psi}(f)(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi\Big(\frac{t-b}{a}\Big)dt \tag{1}$$

where the variable a is the scale factor used for dilation or compression, variable b is the translation factor and a and b are real numbers. If a is quite low then the signal becomes more contracted which results in a more detailed waveform. By contrast, if a is quite high then the signal becomes more stretched out which results in a less detailed waveform. Therefore variable a will determine how compressed our signal will be for transmission.

The wavelet analysis procedure is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet. The main purpose of the mother wavelet is to provide a source function to generate *daughter* wavelets which are the translated and scaled versions of the mother wavelet – this will always us to recover the original signal by performing an inverse continuous wavelet transform which is useful for our application because the original signal can be recovered from the transmitted compressed signal.

Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. We will now describe the wavelet method.

Assume that $Y(t)$ is the value of an observable time series at time t, where t can take on a continuum of values such as a sensor signal we are monitoring in a building. $Y(t)$ consists of two distinct unobservable parts: a so-called trend $T(t)$ (sometimes called a nonrandom smooth function representing long-term movement or systematic variations in a series) and a stochastic component $X(t)$ (sometimes called the noise process) such that

$$Y(t) = T(t) + X(t) \tag{2}$$

where it is assumed that the expected value of $X(t)$ is zero. Priestly [4] refers to trend T(t) as a tendency to increase (or decrease) steadily over time or to fluctuate in a periodic manner while Kendall [5] asserted that the essential idea of T(t) is that it shall be smooth. The problem of testing for or extracting a trend in the presence of noise is somewhat different from the closely related problem of estimating a function or signal $S(t)$ buried in noise. While the model $Y(t) = S(t)+X(t)$ has the same form as equation (2), in general $S(t)$ is not constrained to be smooth and thus can very well have discontinuities and/or rapid variations.

The detection and estimation of trends in the presence of stochastic noise arises in building monitoring data e.g in a temperate climate solar gains can rapidly undergo large changes which can cause large spikes in the internal air temperature signal. This may cause the heating and cooling plant to cycle unnecessarily. A wavelet analysis is a transformation of $Y(t)$ in which we obtain two types of coefficients: wavelet coefficients and scaling coefficients - these are sometimes referred to as the *mother* and *father wavelet coefficients* respectively. The mother wavelet is the primary function while the father is secondary. The wavelets are scaled and translated copies (*father wavelets*) of a finite-length or fast-decaying oscillating waveform (*mother wavelet*). Each wavelet type will have a mother and father wavelet.

The mother and father wavelets coefficients are fully equivalent to the original time series because we can use them to reconstruct $Y(t)$ which is useful for our application. Wavelet coefficients are related to changes of averages over specific scales, whereas scaling coefficients can be associated with averages on a specified scale. The information that these coefficients capture agrees well with the notion of a trend because the scale that is associated with the scaling coefficients is usually fairly large. Trend analysis with wavelets is to associate the scaling coefficients with the trend $T(t)$ and the wavelet coefficients (particularly those at the smallest scales) with the noise component $X(t)$. A more interesting situation arises when we observe trends with correlated noise and we need to adopt a wavelet prototype function called an analyzing wavelet or mother wavelet. Here temporal or time-related analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. A Continuous Wavelet Transform (CWT) is performed using the mother wavelet which allows us to find the amplitude of “frequency” components at different times [6]. CWT is used to divide a continuous-time function into wavelets and is a convolution of the input data sequence with a set of functions generated by the mother wavelet. Under certain models and choice of wavelet function, the wavelet transform de-correlates the noise process and allows us to simplify the statistical analysis involved.

Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing – indeed, sets of wavelets are generally needed to analyze data fully. A set of *complementary wavelets* will deconstruct the data without gaps or overlap so that the deconstruction process is mathematically reversible – this will allow our compressed data to be decompressed by the recipient. Each wavelet type has a different mother and father wavelet designed to satisfy certain conditions based upon the applications they are being designed for. For the purposes of data compression of building sensor data we require a combination of Shannon and Daubechies wavelets because the Shannon wavelet is perfectly localized in the frequency domain which is ideal for deriving trends in voluminous data and the Daubechies wavelet can be designed with as much smoothness as desired. Moreover, the Shannon and Daubechies wavelets can be adjusted to determine the level of loss in the compression process.

3. Results

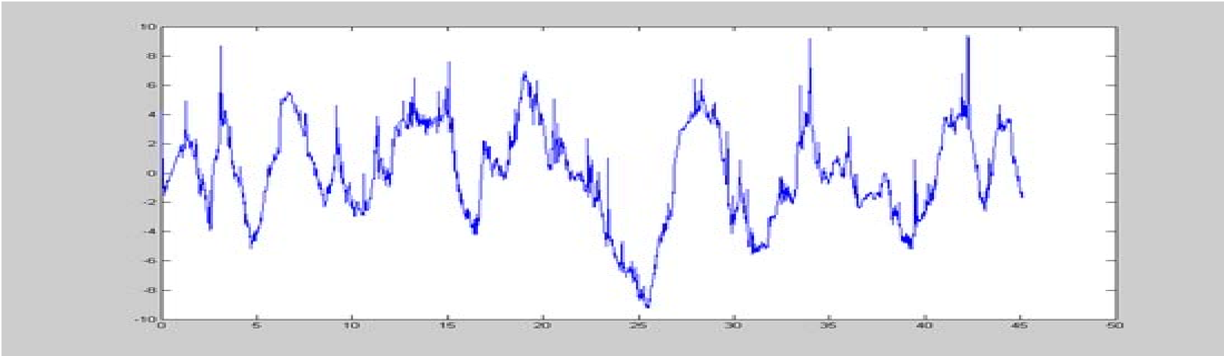

Figure 1 – Original/Raw Data Set

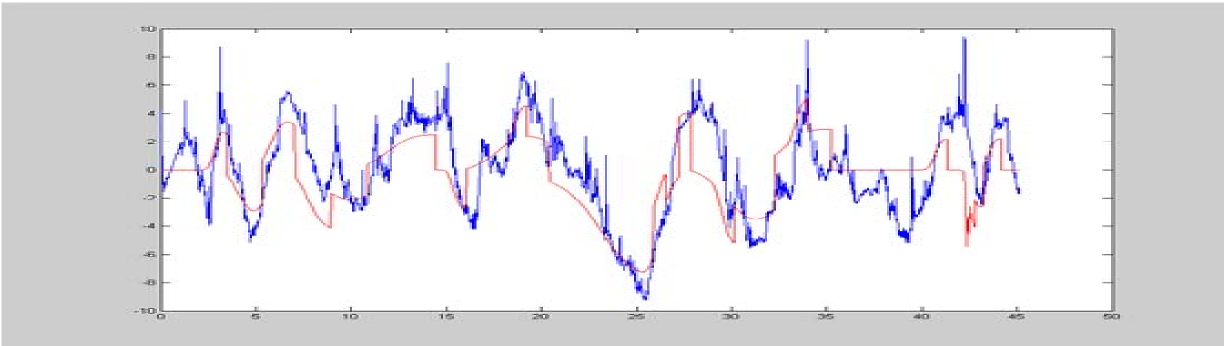

Figure 2 – Final Trends

Figure 1 shows the waveform of an external air temperature signal at 15 - 20Hz recorded on a building in the UK. Outdoor air temperature is an important parameter in the control of building heating, cooling & ventilation systems. It is a much a more noisy signal than indoor environmental parameters and is subject to daily and seasonal cyclical variation and is therefore an appropriate dataset with which to test the wavelet approach to trend detection.

The final trends are captured in figure 2 which clearly mark the data trend when the data was analyzed with Shannon and Daubechies (db6) wavelets. It can be seen that the data has been successfully compressed into trends and that noise has been removed – this data will be transmitted and will make better use of broadband than the original signal.

4. Discussion

Data wavelets compress the high volume, high frequency and noisy data generated by the sensors in a building to provide qualitative measurements in the form of trends – trends not only make better use of bandwidth but have other benefits.

Using data wavelets to generate trends allows us to develop a conceptual model of a complex system (an occupied building), in sufficient detail to enable the facilities manager to make informed decisions about how to improve the buildings operational performance or respond to unexpected events (e.g. an explosion). Such a model would allow temporal and interval-based (qualitative) reasoning which has many applications in environmental monitoring [7].

Temporal reasoning involves 'reasoning about points and intervals of time, quantitative and qualitative relations, common temporal scales, temporal relations with respect to the present and alternate temporal hypotheses' [8]. Therefore, a Building Management System (BMS) can determine if expectations of particular events were met e.g if there is a rapid rise in air temperature due to a sudden increase in solar gains then it could be left to the building's thermal mass to absorb the temperature rise or some other action is required. A BMS can also use past events to draw expectations of what will happen in the future relative to *now*. Using the *past* a BMS can, say, change plans for actions in the future by consolidating on what had already occurred earlier.

Interval-based reasoning removes the burden and complexity of reasoning quantitatively on a point to point basis and allows ongoing processes to be identified by performing qualitative reasoning e.g, from the conceptual model we could derive that a wall is storing heat when the wall internal surface temperature increases faster than the brick interior temperature. Faults can also be identified e.g a rise in air temperature in a supply duct which then remains constant when the external air temperature continues rising above the set point might indicate that the valve controlling hot water flow to the air heater battery has stuck in the fully open position. A BMS can reason about temporal relationships between intervals based on their endpoints – see [9]. This allows a BMS to find associations between different signals with or without the presence of an external event.

5. Summary and Conclusions

We have shown that data wavelets can be used as a lossy data compression technique for building tele-monitoring. Data wavelets allow for more efficient use of network resources – the resulting compressed data reduces storage requirements and makes better use of bandwidth since smaller files take up less room on the access pipe and are therefore faster to transfer over a network. Data compression is ideal for building monitoring in developing countries because it makes better use of lower bandwidth and contention of services at the customer site. We have also shown that our approach serves to remove redundancy in the data such as noise caused by external events.

Our system has potential and its results are encouraging. We believe it to be a step forward in the development of a building tele-monitoring decision support system for compressing and transmitting high volume building sensor data to not only make better use of bandwidth but also enable qualitative reasoning to allow interpretation of building sensor data at a different site.

6. Acknowledgements

The authors thank F. Stevenson, Department of Architecture at Oxford Brookes University, for the use of time series data from a DTI funded project to monitor the performance of a low cost unfired clay brick construction.

7. References

[1] Cisco, 2011, www.youtube.com/watch?v=f1x9qU-Sav8, Accessed 25-01-11.

[2] Moore, M., Foster, P., “China to create largest mega city in the world with 42 million people”, Daily Telegraph, 24/01/11 (2011).

[3] Stallings, W. “Data and Computer Communication 8th Edition”, Pearson Educational Inc. (2007).

[4] Priestley, M.B., “Spectral Analysis and Time Series. (Vol. 1): Univariate Series”, London: Academic Press, (1981).

[5] Kendall, M., “Time Series”, London: Charles Griffin (1973).

[6] Brillinger D., “Some uses of cumulants in wavelet analysis”, Journal of Nonparametric Statistics, 6, 93–114 (1996).

[7] Salatian, A., Adepoju, F., Taylor, B., Odinma, A., “Using Wavelets to Create Conceptual Models from Building Monitor Data’, The 2nd International Multi-Conference on Complexity, Informatics and Cybernetics (IMCIC 2011), Orlando, Florida USA, 1, 235-240 (2011).

[8] Kohane, I.S., Temporal Reasoning in Medical Expert Systems, Boston University School of Medicine, Boston, MA 02118 (1986).

[9] Allen, J. F., “Maintaining Knowledge about Temporal Intervals”, Department of Computer Science, University of Rochester, Rochester, NY 14627, TR 86 (1981).