Model-Based Event Detection in Wireless Sensor Networks

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Abstract—In this paper we present an application of techniques from statistical signal processing to the problem of event detection in wireless sensor networks used for environmental monitoring. The proposed approach uses the well-established Principal Component Analysis (PCA) technique to build a compact model of the observed phenomena that is able to capture daily and seasonal trends in the collected measurements. We then use the divergence between actual measurements and model predictions to detect the existence of discrete events within the collected data streams. Our preliminary results show that this event detection mechanism is sensitive enough to detect the onset of rain events using the temperature modality of a wireless sensor network.

I. INTRODUCTION

A number of testbeds (e.g., [1–3]) have shown the potential of wireless sensor networks (WSNs) to collect environmental data at previously unimaginable spatial and temporal densities. These developments present many data management challenges. First, our experience from the deployments has made clear the shortcomings of the static behavior of current sensor networks. For example, scientists would like to sample the environment at a high frequency to capture detailed information about “interesting” events, but doing so would create an inordinate amount of data. On the other hand, sampling at a lower frequency generates less data but misses important temporal transients. Second, the large amount of data that these networks generate complicates the querying and post-processing stages. Rather than manually traversing through the collected data, scientists would prefer to query for measurements related with certain events (e.g., significant rainfall).

To address these issues, we need WSNs that can reason about the phenomena they observe and change their behavior based on events they detect. Possible adaptation strategies include changes in the sampling rate as well as waking up other nodes in the network to increase spatial coverage of the detected event [4, 5].

The readings of sensors are superpositions of several processes. They are often dominated by predictable foregrounds, which can be very much larger than the subtle trends and variations that we are trying to measure or the small events that we try to detect. In order to interpret the readings, it is important to separate these different signals into independent components. In environmental monitoring, most sensors witness daily variations of all quantities and seasonal trends. In addition, there are discrete natural events (storm, rainfall, strong winds) that have a separable effect on our data. We present an approach using techniques of statistical signal processing to decompose the sensor readings into various physically meaningful components. In our approach, we perform a step-by-step identification of various foregrounds. We identify the diurnal cycle present in both the box and soil temperature sensor data and we account for the effect of seasonal drift. We make use of all these priors (daily cycle, seasonal drift) to detect events by identifying when measurements diverge from those expected by the foregrounds.

Specifically, we explore variants of Principal Components Analysis (PCA) [6] that we use to extract features from the data collected by the network and discover the multiple underlying physical processes that generate the observed data. This produces a model of “normal behavior.” Observations that diverge from the model correspond well with events. We note that one can build the PCA model offline using historical data and that a small number of parameters summarize the phenomena that the motes sense. Such a compact representation of the model makes it possible to build a lightweight event detection mechanism that runs in real time on the network’s motes.

We evaluate the performance of the proposed mechanism using data from the Life Under Your Feet environmental sensing network [1]. We execute the event detection algorithm to detect rain events with the deployment area over ten months of the network’s lifetime. We compare the list of detected events with precipitation data recorded by a weather station at BWI airport.

This specific application reveals another aspect of the proposed approach: while the motes in our network have soil moisture sensors, these sensors cannot detect the onset of a rain event, because soil moisture rises only after the water seeps through the soil. Instead, we use a combination of air and soil temperature measurements to detect when rain starts to fall. Figure 1 shows that temperature varies immediately with the onset of an event, but that soil moisture lags by several hours. The model allows us to detect the rain event rapidly based on indirect evidence prior to the rain’s direct
effect on soil moisture. This better describes system behavior, capturing much more information about the dynamics of soil moisture in response to rain.

A. Environmental Sensing

While our solution is generally applicable to WSNs that collect large amounts of data using multiple sensing modalities, we present our design through a environmental monitoring application we developed and is currently deployed for over 18 months at an urban forest in Baltimore, MD. The purpose of the Life Under Your Feet network is soil monitoring in which each of the network’s ten motes periodically collects measurements, including soil temperature and soil humidity, as well as ambient temperature and light.

The key difference between this application and previous environmental monitoring networks (e.g., [2, 3]) is that all raw measurements are reliably retrieved at the network’s base station, which subsequently inserts them to an SQL database. This stringent reliability requirement is dictated by our scientific collaborators and the research mission of the monitored site. Each mote takes measurements at one minute intervals and records them temporarily to its integrated flash memory. The MicaZ motes we use have a total capacity of 512 KB of flash storage [7]. In general, each mote stores 23 KB of measurement data per day, which indicates that measurement data will be lost if not collected within 20 days. In practice, we download data from each of the network’s motes at least once a week, using an automatic repeat request (ARQ) protocol to ensure reliable delivery in the presence of packet losses.

We also extract weather information (air temperature and rain events) from a weather station at the BWI airport located 25 miles away from our deployment site. The data scraping program we use inserts this data into the same database, allowing meteorological information, such as rain duration and amount of rainfall, to be correlated to the data collected by the sensor network.

II. RELATED WORK

PCA event detection constructs a model of system behavior. We consider two applications of model-based event detection in describing related work. The first is an offline variant in which event detection happens at the database that stores the measurements collected by the network and is used to automatically identify “interesting” regions within the swaths of data acquired by the sensor network. The other is online in that motes in the network detect use events and models to alter their behavior.

Offline event detection provides a model suitable for querying events from noisy and imprecise data. Both database systems [8,9] and sensor networks [10–12] have explored model-based queries as a method for dealing with irregular or unreliable data. Models in these systems include Gaussian-processes [10], interpolation [13, 14], regression [10, 15] and dynamic-probabilistic models [9, 11]. We give another, PCA-based model specifically suited to event detection. MauveDB [9] provides a user-view interface to model-based queries, which greatly extends the utility and usability of models. We intend to implement our offline PCA model within the MauveDB framework.

In the online case, sensor networks reduce the bandwidth requirements of data collection by suppressing results that conform to the model or compressing the data stream through a model representation. This has coincident benefits on resource and energy usage within the network. If sensors measure spatially correlated values, values collected from a subset of nodes can be used to materialize the uncollected values from other nodes [16, 17]. Similarly, temporally-correlated values may be collected infrequently and missing values interpolated [11, 18]. By placing models in the mote itself, the mote may transmit model parameters in lieu of the data, compressing or suppressing entirely the data stream [19–21]. Our PCA model may be used for suppression and compression and may also be used to alter the behavior and configuration of the network, e.g., only collecting data when events occur and turning off large portions of the network at other times.

Most research on “event detection” describes data fusion and in-network event processing, rather than the detection of an event based on the data. REED provides in-network joins to report event conditions that are programmed declaratively [22]. Other systems make sure that multiple sensors detect an event prior to reporting it [23, 24]. Our work focuses on using PCA models to rapidly and accurately report an event at a single mote. This single mote report serves as an input to fusion and event query evaluation. Other ecological monitoring systems use simple rising edge or trigger/threshold based event detectors at each mote [25].

We use PCA to determine that a reading or time series is dissimilar to the normal behavior of the system, characterize by the principal components. Similar uses of PCA include anomaly and intrusion detection in computer networks [26, 27] leakage detection in gas sensor arrays [28]. Recently, PCA has been applied to event detection in the Internet, specifically identifying correlated throughput and loss events on multiple Internet paths [29]. However, the authors provide no details of their approach.
III. METHODOLOGY

Principal component analysis (PCA) [6] or Karhunen-Loève transform (KLT) is a powerful statistical tool for simplifying data, by reducing high-dimensional datasets into low-dimensional datasets that approximate the original data. It does so through singular value decomposition (SVD): an orthogonal linear transform of a matrix (the original data) into an equivalent diagonalized matrix. The values of the diagonal matrix are eigenvalues and the corresponding eigenvectors are called basis vectors. The eigenvectors with maximum eigenvalues represent the “most important” dimensions in that these dimensions have the maximum variance and strongest correlation in the dataset. Thus, the data set may be reduced to just those dimensions (eigenvectors) with large eigenvalues. Data analysis may be performed in the lower dimensional representation with good fidelity to results on the original data. The lower dimensional space offers benefits not only in data size, computational complexity, and ease of visualization, but also these vectors represent the “typical” patterns of the data, whereas the residuals correspond to “atypical” behavior. PCA has seen wide-range of applications, including clustering, correlation detection, pattern matching, and data compression.

A. Applying PCA to sensor measurements

We apply our PCA model to air temperature and soil temperature sensor readings. Sensor readings exhibit typical diurnal cycles, which dominate every other signal present. Fig 2 shows the mean-subtracted profile of a typical day for air temperature and soil temperature. We note the rise in temperature as the sun comes out in the morning and the fall in temperature as the sun goes down in the evening for air temperature. We also observe that soil temperature changes lags air temperature changes by several hours, owing to the inertia of the soil. There is a noticeable phase shift between air temperature and soil temperature. This pattern (AC component) is exhibited by all normal (non-event) days of all seasons around the average value (DC component) for that day.

LUYF sensors record measurements once every minute. We aggregate and smooth multiple readings, which produces a data-series with a reading every 10 minutes. We find empirically that a 10 minute average reveals useful information from the data. It smooths transients, yet samples at a relatively high-frequency. This data-series is then converted into an array of vectors such that each vector represents a day’s readings from midnight to midnight. In a given day, we have 144, 10 minute intervals.

We clean the data prior to building the model in order to best characterize the “normal” behavior of the system. We subtract the mean temperature of that given day (calculated separately for each sensor) from each of these vectors and normalize the readings in the RMS sense. Using normalized vectors ensure that the diagonal elements of the correlation matrix are unity. This balances the contribution of summer and winter to the model even though summer days have higher variance. In order to obtain a well-behaved basis, we censor the days which have a lot of inherent noise and jitter from our training set. We apply a simple median filter to get rid of these “bad” days.

After cleaning the data, we perform a SVD on the data to produce our orthogonal eigenvectors (basis vectors) and order these vectors by decreasing eigenvalues. Fig 3 shows the basis obtained for air temperature and soil temperature for the LUYF deployment between the period of September 2005 to July 2006. We find that the first 4 eigenvectors cover 90.95% of the total variation in the air temperature data and 98.89% in the soil temperature data (as defined by the sum of the first four eigenvalues of the diagonal matrix divided by the trace). The first eigenvector accounts for 55% of the total variation.
variation in the air temperature data. The physical meaning of the different eigenvectors are apparent. The first component of the air temperature is a bell shape curve, corresponding to the slow rise of the temperature around 7 am, then cooling after 3pm. The second eigenvector is rising throughout the day monotonically, describing a warming/cooling trend from one day to another. The third vector causes the bell shaped curve of the temperature to slide forward or backward, representing the effect of the seasonal warming and cooling. Finally, the fourth eigenvector is the broadening and shortening of the daily temperature cycle, again a seasonal effect.

The soil has a large inertia in responding to changes in the external temperature, the characteristic timescale is longer than a day. This manifests itself in the fact that the most significant eigenvector is the cooling/warming, and all others (daily cycle, shift and broadening) are substantially suppressed in amplitude and have a significant phase shift.

B. Expansion on the Basis and Long-Term Trends

To complete the model, we factor in the contributions of all sensors over all time. We expand all the daily vectors over the basis vectors. This gives us four coefficients \( (e_{i1}, \ldots, e_{i4}) \) to describe the daily behavior of the temperature for each sensor \( i \) (five, if we add the mean temperature as \( e_{i0} \)). In order to identify long-term trends, we iteratively run a low-pass filter with a fixed width of one week over the different series, resulting in the smooth series \( S_{i0}, \ldots, S_{i4} \). Each of those coefficients we average over all sensors to get the smooth mean \( (S_{0}, S_{1}, \ldots, S_{4}) \). Hereafter, we will use capitals to denote a time series averaged over all the sensors.

The smoothed series exhibit strong correlations. \( S_{3} \) and \( S_{4} \) describe the beginning and the length of daytime, whereas \( S_{2} \) describes the slow warming and cooling trends, associated with the changes of seasons. These smooth trends serve as the background to all the other variations.

C. Event detection

Our general approach to event detection looks at the coefficient of the first eigenvector. We began by looking at the projections of each day’s mean-subtracted air temperature on the first few eigenvectors. Although the first 4 eigenvectors for air temperature represent 90.95% of the total variation in the data, we realized that most of the information is shown by the coefficient of first eigenvector. Thus, we were able to analyze an entire day’s data by looking at the series \( e_{i1} \) thereby achieving a massive compression. We created the data series \( E_1 \), the eigen-coefficient \( e_1 \) for that day averaged over all sensors. We applied a threshold on the \( E_1 \) series to detect events: low values correspond to behavior that differs from the model. We refer to this method as the BASIC method. Although this approach gave us satisfactory results, it does not take into account the seasonal drift.

We improve on the BASIC detector by removing the seasonal drift and running a high pass filter on the \( e_{i1} \) data series. We run the high-pass filter using the difference \( D_1 = E_1 - S_1 \) between the data series \( E_1 \) and the smoothed series \( S_1 \). We refer to this method as the HIGHPASS method. It significantly improves the number of events detected and reduces the number of false negatives.

The last approach we present makes use of the inertia exhibited by the soil temperature. Since soil temperature changes much slower compared to the air temperature, we looked at the differences between the high-pass filtered series, \( D_1 \) for air temperature and the high-pass filtered data series, \( D_3 \) for soil temperature and then set a suitable threshold for detecting events. We refer to this approach as the DELTA method. It significantly outperforms the BASIC and the HIGHPASS methods. We find that because of the inertia shown by soil temperature, the eigen-coefficients \( E_1 \) for soil temperature show sharp changes on the day(s) after the event. This made the event days easier to identify.

IV. Evaluation

We use our model to detect events on the deployment for the period between September 2005 and August 2006 and compare the results with the actual known events recorded by a weather station at Baltimore-Washington International (BWI) airport [30]. We assume that rain at BWI implies rain at Johns Hopkins University, Baltimore which is located 25 miles away. In our evaluation, we only consider rain events which are prominent. For example, we consider event days as days having precipitation greater than 3 mm. We considered 225 days starting from September 17, 2005 and July 20, 2006, and found that 48 events fit this criteria.

There are many other types of events which have also occurred during the days of our sampling: faulty sensors, motes running out of power, etc. Particularly interesting was a period of about 45 days from mid March 06 to the end of April 06 in which there were lots of anomalies in the \( e_1 \) values. This was the result of sporadic direct sunlight heating up the motes. After April, there was enough foliage cover that the motes (located at ground level) were not exposed to the direct heating of the sun.

We focus on the efficiency of detecting the rain events just from temperature data. There is a good physical basis for this: during rainfall the temperature suddenly drops, but once the rain is over it recovers. This produces a large transient on the
We are able to detect most events days, missing only 7 with the Delta method. Again, we focus on recall, given that non-rain events occur and pollute our precision statistics. The precision-recall curves for different threshold values (Figure 5) shows that good recall can be achieved at better than 50% precision. The converse is not true. High recall matches well with our application needs; reporting events when they occur supports network adaptation and identifies interesting regions of data to scientists. In all likelihood, precision and recall would be much improved with more accurate and local weather monitoring – a better “ground truth” – and considering multiple types of events.

### V. Discussion and Future Work

In this paper we present an application of techniques from statistical signal processing to detect the presence of events (e.g., rain events) that deviate from the regular physical patterns witnessed by a sensor network. We do this by using a variant of the Principal Component Analysis (PCA) technique to generate a compact profile for ‘normal’ measurements. We can then compare actual mote measurements with model predictions and classify the instances in which the two diverge significantly as events of interest. We evaluate the performance of the proposed mechanisms using temperature measurements, collected over a year by a small environmental monitoring network, to detect the onset of rain events. Our preliminary results show that this technique is able to detect most rain events, with small number of false positives, even in the presence of large foreground variations and a substantial seasonal drifts.

This is only the beginning—one can carry this approach much further. While we present event detection in its offline setting, the observation that only a small number of components can accurately describe the collected data suggests that the same mechanism can be implemented on the network’s motes. This in turn can result in a light-weight adaptive sampling algorithm that will enable real-life WSN deployments confronted with slowly varying environments as well as sudden, discrete events. Efficient event detection is at the core of any adaptive observing strategy, and we demonstrate how this can be done on today’s WSN platforms.

At this point the method is able to detect global events, i.e. events that all the sensors experience. However, one would like to detect localized events. While it is seemingly possible...
to apply the same PCA technique to detect events experienced by a single mote, it becomes harder to differentiate between an actual event and a malfunctioning sensor. The question is then how much additional information is necessary to separate faults from actual events. The sensors are expected to have variations due to their local environment (located near/far from a stream, sitting on a hillside with a steep gradient, etc.) which will cause small, but consistent, correlated changes. The task is then to find groups of sensors with correlated measurements. We can do so by removing the obvious daily foregrounds, and the long seasonal trends, at which point we expect to see these small correlated differences in the behavior of sensors in the same group. Once such groups are created, we can compare the projected measurements of a mote with the measurements of other group members. If those agree, then a localized event is most likely occurring, otherwise one (or more) of the sensors are faulty.

So far, we completely exclude from the training set, days with partial data in which due to some hardware errors we did not get a reading for every one of the 144 sampling periods. However, it is easy to apply a ‘gappy’ Karhunen-Loéve transformation [31], in which the expansion coefficients can still be computed over a partial support. Doing so, will enable the creation of a more representative compressed model of the measurement data and hopefully lead to higher detection accuracy.

ACKNOWLEDGMENTS

We would like to thank Ching-Wa Yip (JHU, Department of Physics and Astronomy) for making available to us her PCA C# library and providing us her valuable time in the discussions. The data collected here was done in collaboration with Katalin Szlavecz (JHU, Department of Earth and Planetary Science) and Razvan Musaloiu-E (JHU, Department of Computer Science). The on-line database was built in collaboration with Jim Gray and Stuart Ozer (Microsoft Research). Their help and contributions are gratefully acknowledged.

REFERENCES

[1] R. Musaloiu-E., A. Terzis, K. Szlavecz, A. Szlay, J. Cogan, and J. Gray, “Life Under Your Feet: A Wireless Soil Ecology Sensor Network,” in Proceedings of the Third Workshop on Embedded Networked Sensors (EmNets 2006), May 2006.

[2] G. Tolle, J. Polastre, R. Szewczyk, N. Turner, K. Tu, P. Buonadonna, S. Burgess, D. Gay, W. Hong, T. Dawson, and D. Culler, “A Macroscope in the Redwoods,” in Proceedings of the Third ACM Conference on Embedded Networked Sensor Systems (SenSys), Nov. 2005.

[3] A. Mainwaring, J. Polastre, R. Szewczyk, D. Culler, and J. Anderson, “Wireless sensor networks for habitat monitoring,” in Proceedings of 2002 ACM International Workshop on Wireless Sensor Networks and Applications, Sept. 2002.

[4] P. Dutta, M. Grimmer, A. Arora, S. Bibyk, and D. Culler, “Design of a wireless sensor network platform for detecting rare, random, and ephemeral events,” in Proceedings of IPSN, 2005.

[5] L. Gu and J. Stankovic, “Radio triggered wake-up capability for sensor networks,” in Real-Time Applications Symposium, 2004.

[6] R. Duda, P. Hart, and D. Stork, Pattern Classification. Wiley, 2001.

[7] C. Corporation, “MICAz Specifications,” Available at http://www.xbow.com/Support/Support_pdf_files/MICAZ_MIB_Series_Users_Manual.pdf

[8] IBM, “DB2 intelligent miner,” 2007, available at http://www-306.ibm.com/software/data/db2miner/

[9] A. Deshpande and S. Madden, “Mausweb: supporting model-based user views in database systems,” in Proceedings of ACM SIGMOD, 2006.

[10] A. Deshpande, C. Guestrin, S. Madden, J. M. Hellerstein, and W. Hong, “Model-driven data acquisition in sensor networks,” in Proceedings of VLDB, 2004.

[11] A. Jain, E. Change, and Y. Wang, “Adaptive stream resource management using kalman filters,” in Proceedings of ACM SIGMOD, 2004.

[12] M. Chu, H. Hausecker, and F. Zhao, “Scalable information-driven sensor querying and routing for ad hoc heterogeneous sensor networks,” International Journal of High-Performance Computing Applications, vol. 16, no. 3, 2002.

[13] S. Grumbach, P. Rigaux, and L. Segounif, “Manipulating interpolated data is easier than you thought,” in Proceedings of VLDB, 2000.

[14] L. Neugebauer, “Optimization and evaluation of database queries including embedded interpolation procedures,” in Proceedings of SIGMOD, 1991.

[15] C. Guestrin, P. Bodik, R. Thibaix, M. Paskin, and S. Madden, “Distributed Regression: an Efficient Framework for Modeling Sensor Network Data,” in Proceedings of IPSN 2004, Apr. 2004.

[16] H. Gupta, V. Nacda, S. Das, and V. Chowdhary, “Energy-efficient gathering of correlated data in sensor networks,” in Proceedings of MobiHoc, 2005.

[17] Y. Kotidis, “Snapshot queries: towards data-centric sensor networks,” in Proceedings of ICDE, 2005.

[18] A. Deligiannakis, Y. Kotidis, and N. Roussopoulos, “Compressing historical information in sensor networks,” in Proceedings of SIGMOD, 2004.

[19] D. Chu, A. Deshpande, J. Hellerstein, and W. Hong, “Approximate data collection in sensor networks using probabilistic models,” in Proceedings of ICDE, 2006.

[20] A. Silverstein, R. Braynard, G. Filpus, G. Puggioni, A. Gelfand, K. Munagala, and J. Yang, “Data-driven processing in sensor networks,” in Proceedings of Conference on Innovative Data Systems Research, 2007.

[21] D. Tulone and S. Madden, “PAQ: Time series forecasting for approximate query answering in sensor networks,” in Proceedings of the European Conference on Wireless Sensor Networks, 2006.

[22] D. J. Abadi, S. Madden, and W. Lindner, “Reed: Robust, efficient filtering and event detection in sensor networks,” in Proceedings of VLDB, 2005.

[23] S. Li, Y. L. and S. H. Son, J. A. Stankovic, and Y. Wei, “Event detection services using data service middleware in distributed sensor networks,” in Proceedings of IPSN, 2003.

[24] A. Herboldt, T. Lamarrne, N. Bulusu, and S. Jha, “Resilient event detection in wireless sensor networks,” in Proceedings of Intelligent Sensors, Sensor Networks and Information Processing, 2004.

[25] R. Szewczyk, E. Osterweil, J. Polastre, M. Hamilton, A. Mainwaring, and D. Estrin, “Habitat monitoring with sensor networks,” ACM, vol. 47, no. 6, 2004.

[26] W. Wang, X. Guan, and Z. Zhang, “A novel intrusion detection method based on principle component analysis in computer security,” in Proceedings of Advanced in Neural Networks, 2004.

[27] A. Lakhina, M. Crovella, and C. Diot, “Mining anomalies using traffic feature distributions,” in Proceedings of ACM SIGCOMM 2005, Aug. 2005, pp. 217–228. [Online]. Available: http://www.cs.bu.edu/faculty/crovella/paper-archive/sigc05-mining-anomalies.pdf

[28] A. Perera, N. Papamichail, N. Bärsvan, U. Weimar, and S. Marco, “On-the-fly processing of scientific data using a sensor network,” in Proceedings of the Third Workshop on Sensor Network Applications and Systems, 2006.

[29] D. J. Abadi, S. Madden, and W. Lindner, “Reed: Robust, efficient filtering and event detection in sensor networks,” in Proceedings of VLDB, 2005.

[30] A. Jain, E. Change, and Y. Wang, “Adaptive stream resource management using kalman filters,” in Proceedings of ACM SIGMOD, 2004.

[31] A. J. Connolly and A. S. Szalay, “A Robust Classification of Galaxy Spectra: Dealing with Noisy and Incomplete Data,” in Proceedings of IPSN 2004, Apr. 2004.