Intelligent Contextual Data Stream Monitoring

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ABSTRACT

Contextual data monitoring plays an important role in increasing the quality of life of humans. Sensors observing specific activities report contextual data to a central system capable of situational reasoning. The system responds to any event related to the observed phenomenon. We propose an intelligent mechanism that builds on top of sensors measurements and derives the appropriate decisions for immediate identification of events. The mechanism adopts multivariate data fusion, time-series prediction, and consensus theory for aggregating measurements. We adopt Fuzzy Logic for handling the induced uncertainty in the decision making on the derived alerts. Simulations over real contextual data showcase the advantages and disadvantages of our monitoring mechanism.

Categories and Subject Descriptors

H.3.3 [**Information Systems Applications**]: Sensor Networks

Keywords

Fuzzy logic, time-series prediction, data fusion, consensus theory.

1. INTRODUCTION

A Monitoring System (MS) can monitor specific contextual parameter and generate alerts when any abnormalities occur. Alerts are derived by triggering mechanisms that continuously check the fulfilment of certain conditions. For instance, sensors observing physiological activities measure specific health parameters, while an MS reasons over the observed values and takes decisions for each abnormality. Such decisions could be either short- or long-term. Short-term decisions are made in short time just after the identification of an event. Long-term decisions are related to reasoning when processing data and no immediate response is necessary, e.g., the MS could decide the appropriate time that specific measures should be taken in order to avoid further problems. Example application domains involve the monitoring of health data (e.g., sleep issues [6], the estimation and classification of health conditions [20], and emotion recognition [10]), security or environmental monitoring [13], [18].

In this paper, we consider an MS receiving input from a set of sensors that observe a specific phenomenon. Sensors send their observations at specific intervals to the MS. The MS based on observations should derive the *Degree of Alert* (DoA) that indicates if measures should be applied. The MS should also minimize false alerts as those can affect the performance of the entire system. The most important consequence is that if measures are applied in a wrong interval, they will not benefit the performance of the response. If the MS is capable of identifying the right time to derive the alert, then the impact of the measures will be maximized. The MS handles sensors as a team and tries to take the appropriate decision based on the team opinion. We propose the combination of multivariate contextual data fusion techniques, time-series forecast and consensus theory. Fusion provides an efficient means for aggregating individuals (sensors) opinion into a final fused value. Time-series prediction is adopted to handle missing values as sensors can be affected by a number of issues like their resources state, the environment's characteristics, thus, some measurements could not be present. Our mechanism derives knowledge from the team of sensors and does not rely on single sensor observations. A single sensor could be affected by various reasons (e.g., network connection, battery level) and its reports could not be valid. Consensus is then adopted to reveal the unanimity among sensors about their observations. We also adopt Fuzzy Logic (FL) to handle the uncertainty related to sensors measurements. Our mechanism is capable of incorporating into the decision mechanism current and past behaviour of the measurement patterns, while manages the induced uncertainty. The FL provides outputs that are adopted to guide prognostic actions.

2. RELATED WORK

A set of data mining models are proposed for managing the data retrieved by wearable sensors [1]. Sensors placed in a human body consists a Body Sensor Network (BSN) [17]. The BSN senses health parameters while the MS is responsible for data aggregation, fault tolerance, etc. A BSN could be adopted to monitor physiological data [11] and can be used for medical exploration [14]. The sensor network can also monitor elderly people's behavior [7], [8].

Sensors allow freedom in the movement of subjects and doctors to identify symptoms in the minimum time [13]. In addition, sensors networks facilitate a high quality of life compared to treatment centers [3]. In such systems, FL can cover the uncertainty related to sensors measurements and be the basis for building intelligent decision making mechanisms. In [5], the authors discuss a FL-based solution and presents a loopback feature in order to constantly improve fuzzy logic rules, knowledge base, and generated recommendations. In [16], a FL Controller (FLC) that receives sensor contextual information and outputs linguistic decisions sent to patient/doctor is designed. In environmental monitoring, FL could also be proved a useful technique for supporting high quality systems. In [13], the authors report on a model that predicts the peak particle velocity of ground vibration levels. Another prediction model is discussed in [18]. The model tries to predict the Gamma radiation levels in air while the adoption of the FL aims to provide a method for handling possible missing values.

3. RATIONALE & CONTRIBUTION

Consider a set of N sensors $\mathcal{S} = S_1, S_2, \ldots, S_N$ that monitor a specific phenomenon and report their observations $x_1, x_2, \ldots, x_N$ to an MS. We assume that sensors observe the same phenomenon and their reports are sent at predefined intervals. When the MS receives the reports, it decides if an event is identified, thus, it derives alerts without any human intervention. The MS is not based only on a single sensor observations, as false alarms could be derived. Sensors could report invalid observations due to various reasons like resources status and environmental characteristics. The MS handles $\mathcal{S}$ as a *team* and, through team reports, tries to minimize false alarms while maximizing the performance (i.e., event identification). The MS should rely on the *opinion* of the majority before it decides the initiation of an alert. A number of components are responsible to manage the incoming contextual data and derive the appropriate decision. These components are: (i) The **Prediction module (PM)**. The PM, based on sensors historical values, predicts future observations when missing values are present; (ii) The **Fusion module (FM)**. The FM undertakes the responsibility of eliminating the outliers data and providing the final fused measurement; (iii) The **Consensus module (CM)**. The CM produces the **Degree of Consensus** (DoC), which denotes the unanimity in the opinion of the sensors (experts). We consider DoC $\in [0, 1]$ where DoC $\rightarrow 1$ indicates that most of the sensors agree on their inference about the occurrence of a phenomenon; (iv) The **FL module (FLM)**. The FLM combines the outputs of the FM and the CM and derives the **Degree of Alert** (DoA). The DoA provides a support for deriving an alert to users or applications. The decision is made based on (1) the current aggregated measurements and (2) the consensus of the team. When the DoA is over a predefined threshold, the MS identifies the corresponding event and, then, initiates an alert to end users.

Our major contribution is an MS that minimizes false alarms without any human intervention. It relies on the opinion of the team and not just on simple thresholds. The adoption of the FL provides the MS with the necessary uncertainty management of contextual data concerning the case where the alert should be immediately triggered.

4. THE PROPOSED MECHANISM

Uncertainty is observed in many aspects that relates to the sensors measurements reported to the MS. Sensors could be affected by many issues and, thus, they could report faulty values about the observed phenomenon. Main reasons are the different views on the observed phenomenon as experienced by sensors and the existence of noise in measurements. Our mechanism deals with uncertainty by firstly adopting time-series prediction techniques for missing values. Prediction is applied in the historical observations of each sensor. Accordingly, a fusion process is adopted to eliminate the outliers and outputs an aggregated measurement based on the confidence on the sensors observations. In the sequel, the mechanism involves a consensus process that depicts the unanimity in the sensors opinion (observations) for a specific phenomenon. Finally, we incorporate an uncertainty handling technique based on Fuzzy Sets for deriving the DoA based on the previously described modules.

Prediction Module: Consider the discrete time domain $\mathbb{T}$ with reporting time $t \in \mathbb{T}$ at which the mechanism (i) receives contextual sensor data and (ii) triggers the fusion, consensus and FL modules. If the MS identifies that a sensor does not report any value, it is based on historical values and estimates the current sensor's observation. This means that for sensor $S_i \in \mathcal{S}$ a time ordered set of past values $\mathcal{H}_{S_i}$ is maintained. Since the MS should derive the DoA in the minimum time (i.e., the provision of alerts should be realized in (near) real time due to the criticality of the applications), we adopt a linear time-series predictor. We focus on a sensor $S_i \in \mathcal{S}$ and consider the history of the latest M observations $x_i(t-1), x_i(t-2), \ldots, x_i(t-M)$. We predict the **missing measurement** $\hat{x}_i(t)$ through a linear combination of the $x_i(t-k)$ historical measurements with real-valued a_k prediction coefficients. The set of coefficients a_k, $k = 1, \ldots, M$ are estimated to minimize the prediction error between the predicted $\hat{x}_i(t)$ and the actual measurement $x_i(t)$ at the reporting time t, with $\hat{x}_i(t) = \sum_{k=1}^{M} a_k x_i(t-k)$. A number of algorithms have been proposed for the calculation of the a_k coefficients, with most known being the minimum mean square estimate. Based on this minimization process we get a number of equations, known as Yule-Walker equations through which they provide estimates on the a_k coefficients. In our effort, we adopt the Levinson-Durbin algorithm.

Fusion Module: Data fusion combines contextual data from all sensors in $\mathcal{S}$ to derive reliable fused measurements. We adopt the cumulative sum (CumSum) concept drift algorithm [15] for outliers detection over all measurements and the linear opinion pool algorithm [12] for deriving the final aggregated value. The CumSum algorithm detects if there is any change in the distribution of a contextual time series $x_i(t)$ corresponding to sensor $S_i \in \mathcal{S}$. The algorithm is a change-point detection technique based on the cumulative sum of the differences between the current value at instance t and the overall average up to t. Slopes depict jumps in the times series, thus, corresponding to outliers. This is very important as outliers define variation in data and, thus, the detection of changes becomes very difficult. We adopt a two-side detection scheme where $x_i(t)$ is inferred as an outlier when it deviates above a target threshold h^+ or below a target threshold h^-. The parameters of the algorithm are: (i) the target value (i.e., the mean value), (ii) the tolerance for the above and below thresholds k^+, k^- and, (iii) the thresholds h^+, h^-. Two signals are the outputs of the Cum-

Sum algorithm: the first is related to the above detection signal $g^+ \in \{0, 1\}$ while the second corresponds to the below detection signal $g^- \in \{0, 1\}$. When the time series $x_i(t)$ deviates from the thresholds, g^+ and g^- are set to 1. When the time series are in the specified thresholds, g^+ and g^- are both set to 0. The detected outliers (i.e., when g^+ and g^- set to 1) are eliminated and, thus, the mechanism at t is based on the opinion (measurements) of those sensors that do not produce outliers.

The MS adopts a linear opinion pool scheme for the remaining values. The linear opinion pool is a standard approach to combine experts' opinion through a weighted linear average. It is used in many application domains where there is the need for combination of experts' opinion that, probably, they are not always in agreement. The final aim is to combine single experts' opinions to produce the opinion of the team. In our case, we apply specific weights in each expert to 'pay more attention' on her opinion affecting more the final result. We select this scheme for its simplicity and accuracy. Since experts (sensors) are not always in agreement, belief aggregation methods are used to derive the final result. Formally, the **fused measurement** $f = \mathcal{F}(x_1, \ldots, x_N)$ is the opinion pool based on the pooling operator $\mathcal{F}$ over the measurements (opinions). We adopt a weighted linear average, i.e., $f = \mathcal{F}(x_1, \ldots, x_N) = \sum_{i=1}^{m \leq N} \lambda_i x_i$, where $\lambda_i \in [0, 1]$ is the weight associated with the opinion of sensor S_i, which does not produce an outlier as indicated by the CumSum algorithm, and $\sum_{i=1}^{m \leq N} \lambda_i = 1$. Weights are calculated based on the specific characteristics of each sensor. We define C_i representing the confidence that the MS has to sensor S_i in the team in successfully fulfilling the assigned task. Hence, $\lambda_i = \frac{C_i}{\sum_{j=1}^{m \leq N} C_j}$, where $m \leq N$ is the number of sensors retrieved by the CumSum algorithm.

We adopt a simple heuristic for calculating C_i. Assume that S_i is considered as outlier m_i times for a window W. As the mechanism cannot be certain on the real state of sensors, we try to disregard sensors that for successive measurements report outliers. We adopt a reverse sigmoid function for evaluating C_i, i.e., $C_i = \frac{1}{1+e^{\gamma(m_i - \delta)}}$, where γ and δ are real-valued parameters defining the shape and the threshold for eliminating the confidence of a sensor, respectively. The mechanism calculates m_i every time instance t a fusion process takes place. Over the threshold, depicted by δ, the C_i is eliminated. This means that if a sensor is considered as outlier for $m_i > \delta$ times, the mechanism decreases the confidence level of that sensor.

Consensus Module: The consensus module evaluates the Degree of Consensus (DoC), DoC $\in [0, 1]$. The DoC represents the unanimity on the opinion of sensors about the observed phenomenon. When DoC $\to 1$, it indicates a team of sensors that unanimously agree on a specific opinion (i.e., occurrence or non-occurrence) about a phenomenon. A DoC $\to 0$ denotes a team of sensors that cannot conclude on the same opinion. Sensors have their own opinion about the phenomenon realized by their measurements. The mechanism identifies whether there is a consensus on the team to be capable of deriving certain decisions on events. The evaluation of the DoC is based on [4], which compares the opinion of each team sensor with the remaining ones. The DoC at reporting time instance t is defined as $DoC = 1 - \frac{1}{2n^2} \sum_{\forall i,j,i \neq j} (x_i - x_j)^2$, where x_i and x_j are measurement from sensors S_i and S_j, respectively.

Table 1: The proposed FL rule base

No.	f	DoC	DoA
1	Low	Low	Low
2	Low	Medium	Low
3	Low	High	Medium
4	Medium	Low	Medium
5	Medium	Medium	Medium
6	Medium	High	Medium
7	High	Low	High
8	High	Medium	High
9	High	High	High

Fuzzy Logic Module: We propose a FL Module (FLM), which defines the MS reaction to the incoming data. We adopt the Mamdani fuzzy inference, where each fuzzy rule has the following form: R_j: IF u_{1j} is A_{1j} AND u_{2j} is A_{2j} AND ... AND u_{lj} is A_{lj} THEN y_{1j} is B_{1j} AND ... AND y_{mj} is B_{mj} where R_j is the jth fuzzy rule, u_{ij} $(i = 1, \ldots, l)$ are the inputs of the jth rule, y_{kj} $(k = 1, \ldots, m)$ are the outputs of the jth rule and A_{ij} and B_{kj} are membership functions associated with linguistic terms.

The FLM takes two inputs: (i) the fused measurement f and (ii) the DoC, while the output is the DoA value. Without loss of generality, we assume that inputs are normalized in the interval $[0, 1]$ based on minimum and maximum values as depicted by the application domain. We also consider that DoA $\in [0, 1]$, with DoA $\to 1$ indicating that the danger is at high levels; the opposite stands when DoA $\to 0$. For inputs and the output, we consider three linguistic values: Low, Medium, High. A Low value represents that the fuzzy variable takes values close to the lower limit while a High value depicts the case where the variable takes values close to the upper level. A Medium value depicts the case where the variable takes values close to the average (i.e., around 0.5). We consider triangular membership functions as they are widely adopted in the literature. Note, our mechanism is generic enough, thus, any membership function that better suits to the application domain can be adopted. The FLM fuzzifies the inputs and proceeds with fuzzy inference which involves a set of fuzzy rules that result the DoA value. These rules are defined by experts and incorporate a human view on the decision process that the MS should follow. Table 1 shows the proposed FL rule base, where the rules are designed for scenarios in which sensors data reaching the upper limit exhibit a 'danger' case. The FLM output relates to de-fuzzification for deriving the DoA. If, at time t, the DoA is over a predefined threshold, the MS triggers an alert, otherwise, it proceeds with the upcoming sensors' measurements.

5. EXPERIMENTAL RESULTS

We examine the MS performance related to the Rate of False Alerts (RFA). RFA $\in$ [0,1] represents the rate of false alerts derived by the MS. As RFA $\to 1$, the MS results a lot of false alerts and no efficient conclusion could be drawn from such responses about the true state of the phenomenon. As RFA $\to 0$, the MS minimizes the rate of false alerts, thus, efficient conclusions could be drawn. The RFA metric is defined as the ratio of the number of false alerts out of the number of measurements for a certain period. We experiment with two datasets. The MHEALTH dataset [2] comprises vital signs recordings for ten volunteers ($N = 10$). We adopt

Table 2: RFA for our MS and SSA

p	MHEALTH Dataset RFA_{SSA}	MHEALTH Dataset RFA_{FLM}	Intel Berkeley Dataset RFA_{SSA}	Intel Berkeley Dataset RFA_{FLM}
1%	34	0	58	0
5%	133	0	179	0
10%	217	2	356	0
20%	358	3	535	0
40%	560	22	755	3
60%	682	47	831	10

the measurements corresponding to cases where volunteers are standing still, sitting or lying down. We consider the provided electrocardiogram signal and assume 1,000 measurements for each volunteer. As these signals define values close to zero, we apply data transformation by adding a base value (e.g., 10). The second dataset is retrieved by the Intel Berkeley Research Lab [1], which contains millions of temperature measurements retrieved by 54 sensors. We get 15,000 measurements assuming that $N = 15$ sensors produced 1,000 reports. All measurements are normalized. As no event is depicted in both datasets, we consider the injection of faulty values to examine whether the MS will produce false alerts. We inject faulty or missing measurements as indicated in [19] by replacing a true value x_i with $\tilde{x}_i = (r + 1)x_i$ where $r \in \{2, 5, 10\}$ or with a missing one with probability $p \in \{1\%, 5\%, 10\%, 20\%, 40\%, 60\%\}$. For instance, when $p = 1\%$, we inject 100 both missing and faulty measurements. We compare the proposed MS with the Single Sensor Alerting (SSA) mechanism. The SSA mechanism delivers an alert when at least one sensor reports a value over a predefined threshold. We set the threshold equal to 0.7. Table 2 shows the RFA for our mechanism and SSA. Our mechanism produces a low number of false alerts compared to the SSA. For $p \in \{1\%, 5\%\}$ for the MHEALTH dataset and $p \in \{1\%, 5\%, 10\%, 20\%\}$ for the Intel Berkeley dataset, our MS does not produce any false alert. Another interesting observation is that our MS produces less false alerts when we adopt the Intel Berkeley dataset. The average number of the alerts is 12 for the MHEALTH dataset and 2 for the Intel Berkeley dataset.

6. CONCLUSIONS

We propose a mechanism that combines certain intelligent methods for handling sensors measurements in a MS with the aim to avoid false alerts. We adopt time-series prediction for eliminating missing values and multivariate fusion techniques for aggregating sensors observations while outliers are discarded. A consensus technique is adopted to derive the unanimity level of sensors measurements. The adoption of FL to our mechanism provides efficient decision making that handles the uncertainty present in such scenarios. Simulations over real data exhibit the performance of our system by minimizing false alerts.

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