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SPECIAL SECTION ON RECENT ADVANCES IN COMPUTATIONAL INTELLIGENCE PARADIGMS FOR SECURITY AND PRIVACY FOR FOG AND MOBILE EDGE COMPUTING

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Fog Intelligence for Real-Time IoT Sensor Data Analytics

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ABSTRACT The evolution of the Internet of things and the continuing increase in the number of sensors connected to the Internet impose big challenges regarding the management of the resulting deluge of data and network latency. Uploading sensor data over the web does not add value. Therefore, an efficient knowledge extraction technique is badly needed to reduce the amount of data transfer and to help simplify the process of knowledge management. Homoscedasticity and statistical features extraction are introduced in this paper as novelty detection enabling techniques, which help extract the important events in sensor data in real time when used with neural classifiers. Experiments have been conducted on a fog computing platform. System performance has been also evaluated on an occupancy data set and showed promising results.

INDEX TERMS Fog computing, novelty detection, sensor signals, Internet of Things (IoT), Levenes test, statistical features.

I. INTRODUCTION

IoT computing paradigm shift is evolving and moving from the cloud computing, fog computing towards edge computing. The paradigm shift will be imposed by the need to: reduce transmission cost; avoid network latency; enhance security and privacy and many other benefits. However, remains the scalability, and failure risks issues. IoT computing takes place at three levels: edge computing (i.e. lowest level) near a data/information source; fog computing (i.e. intermediate level) occurs in IoT Gateway or LAN; and cloud computing (i.e. highest level) which on the cloud server. For example, edge computing as in a smartphone uses its camera to detect faces and objects. In fog computing, a Gateway could collect, and/or de-noise and/or analyze sensors data and make a decision. A good example is the Amazon Echo or Google Assistant. In cloud computing, the sensor data analytics is performed on a remote cloud server.

Novelty detection in sensor signals is playing a crucial role with the increasing number of sensors connected through the IoT in order to reduce the amount of data that need to be analyzed and consequently decreasing the cost of both data storage, transmission, and processing in the cloud. Novelty detection in continuous sensor data streams is a challenging problem. A highly discriminant feature set has to be extracted to reflect any sudden event in sensor signals. These features should be easy to compute with short computational time to be able to classify the signal in real-time.

In this paper, seven features have been extracted and fed into a neural network for signal classification and consequently, event detection at the fog level. Signals are classified to either normal sensor signals (no novelty) or abnormal signals with novelty. Once an event has been detected, the owner of the sensor has to be alerted. This is important in case an intruder switches lights on in a smart home, or gas leakage occurs or fire is detected or unauthorized motion detected, an alert sent to the users mobile phone. Here, a GSM GPRS module (SIM900) [1] is used to send SMS messages to sensor owners when there is any novelty detected based on sensor

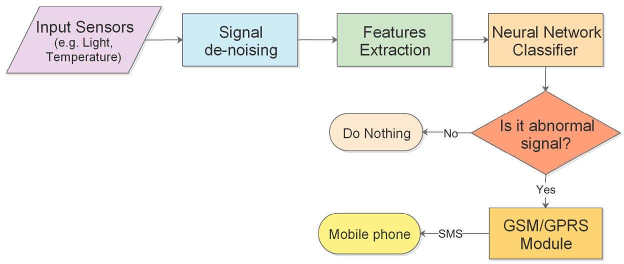

FIGURE 1. Layout of the event detection and communication system.

data analytics. The module uses a SIM card for the communication exactly as a mobile phone. Figure 1 shows the layout of a system proposed for data analytics at the device level and sending the important events only to the concerned users.

The main contributions of this paper can be summarized as follows: (1) we present a fog-level IoT analytic system for detecting signal abnormality; (2) we introduced a set of homoscedasticity and statistical features that can be effectively computed in real-time; (3) we examine the system on a large-scale real data collected from different types of sensors. The proposed system can be used as a foundation for future development of many IoT applications which are based on sensor data analytics such as motion, fire, or occupancy detection.

The rest of this paper is organized as follows. Related works are described in Section II. In Section III, a signal de-noising method is introduced as a preprocessing step. The feature extraction methods and the neural networks classifier are described in Section IV and V respectively. The experiential results, discussion, and conclusion are provided in Sections VI and VII.

II. RELATED WORKS

Fog data mining is an important strategy for IoT in order to reduce the cloud storage requirement, the energy consumption, and package transformation across the wireless network. Each individual sensor or a set of sensors carries out sort of low-power processing on the acquired data to discover the novelty patterns. Authors in [2] introduced the concept of edge mining for IoT and studied the efficiency of three different edge mining methods on data transmission and energy reduction.

Edge data mining approaches can be categorized into time-series forecasting, and event- based approaches. In time-series forecasting, two prediction models are working synchronously in the sensor-level and sink (i.e. the base station) nodes where the time-series data is analyzed on the low-level sensors to detect anomalies. The data is only sent to the sink node if the measurement data is different from the predicted one by some constant. Many approaches have been used including stochastic, and regression-based methods. For example, authors in [3] and [4] used Kalman filter and dynamic probabilistic model respectively to reduce data transmission rate from sensor nodes. In [5], authors extend the prior dual model prediction on sensors and sink by transmitting only a state vector estimate instead of the raw

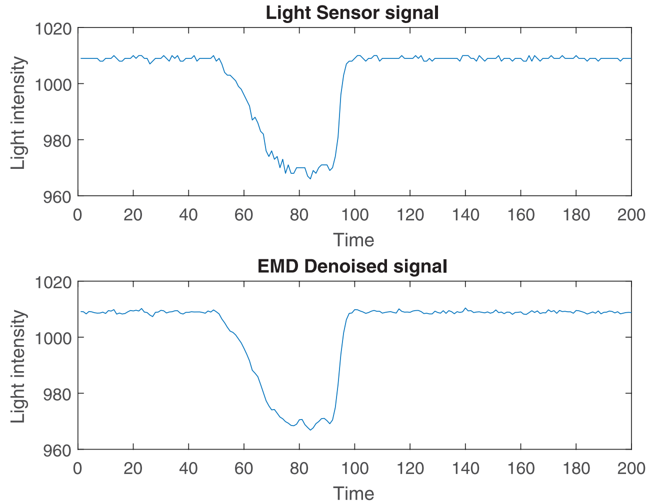

FIGURE 2. LDR Signal (top) and de-noised signal (bottom) using empirical mode decomposition.

data when the error on the sink node exceeds a constant value. In [6] and [7], authors used Auto-Regressive (AR) model to reduce the processing achieved by sensors and limit the transmitted data to be the coefficients of the model. In [8], authors introduced a simple linear model called derivative-based prediction to predicate the data by computing the gradient of the ending points of a collected data over a short period. Regression-based methods are much simpler than stochastic based methods and easy to implement.

The event-based approaches work similarly to time-series forecasting, but it does not have to replicate all the data generated in the sensor-level on the sink node. The raw data is quantized into some events or categories, and it only pushes the data to the sink node when these events happened. For examples, in [9], authors introduced a postural activity monitoring system that recognizes nine different human postures from the accelerometer data using a decision tree algorithm. Similarly in [10], proposed fall detection system for elderly people based on accelerometers and gyroscopes data. In [11], accelerometers reading is used to detect railway bridge health. In [12], real-time forest fire detection is proposed based on neural networks by analyzing in-networking measurements gathered from multiple sensors to predicate weather index that only sent to the sink node. In [13], authors summarized the measurement data as a histogram to reduce the packet reduction ratio. However, most of these methods are directly classifying the raw sensor data which is sensitive to noise and requiring much more time to process.

III. SENSOR SIGNAL DE-NOISING

One of the most powerful filtering techniques for signal de-noising is the empirical mode decomposition (EMD) method [14], [15]. The raw sensor signal is decomposed into a set of intrinsic mode functions (IMFs). In order to consider a signal as IMF, it must have an equal number (or differ by one) of extrema and zero crossing and the upper and lower envelope has zero mean everywhere. The filtered signal z (as

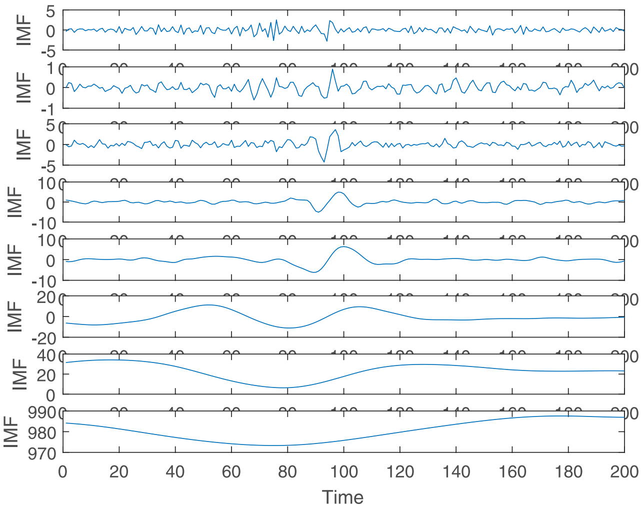

FIGURE 3. Intrinsic Mode functions 1-8 of the LDR signal from top to bottom.

shown in Figure 2) is reconstructed by eliminating the first IMF component according to the following formula:

$$z = \sum_{j=2}^{T} IMF(j) \tag{1}$$

where T is the number of the IMFs. Here, we remove the high-frequency noise which is represented by the first IMF of sensor signals. Figure 2 shows an LDR signal before and after processing by using the EMD. The high frequencies are filtered out, and the valuable features of the signal are remaining. Figure 3 shows the IMFs of the LDR signal and as illustrated the high-frequency noise is represented by the first IMF.

IV. FEATURE EXTRACTION

Efficient feature extraction techniques have been proposed in order to analyze the overwhelming data acquired by any set of sensors. Any novel event in a sensor signal is characterized by a sudden change in signal level. To detect this sudden change, a multitude of dissimilarity/similarity features should be extracted as follows:

A. HOMOSCEDASTICITY MEASURE

Homoscedasticity of sensor signals like e.g. temperature or light is a natural phenomenon. The detection of novelties in sensor signal in the case of a sudden signal change due to an external factor plays a crucial role in monitoring the environmental conditions or smart homes or detecting motion. In this paper, we introduce a new approach for novelty detection using the Levene's test [16]. Levene's test is measuring the homogeneity of variances of samples drawn from two successive windows of sensor signals.

In this work, it is assumed that the sample variances of the same sensor signal windows taken under normal operating conditions without external interruption are equal. The occurrence of a novelty causes the Levene's test to be higher than its normal value indicating that the null hypothesis of equal variances is rejected. Applying EMD technique on the raw sensor signal is ensuring that the proposed technique has less effect on the noise. The F-statistic of Levenes test is used as a measure of homogeneity of variance to detect novelties in a sensor signal. Levene's Test' F-statistic of two successive windows X_k is computed according to the formula

$$F = \frac{N-K}{K-1} \frac{\sum_{k=1}^{K} n_k(\mu_k - \mu_N)^2}{\sum_{k=1}^{K} \sum_{j=1}^{n_k} (d_{kj} - \mu_k)^2} \tag{2}$$

where $K = 2$ in the case of two successive windows, N is the total number of samples in the K windows, n_k is the number of samples in the k-th window (e.g. 100 samples), μ_N is the mean value of all sensor values in all windows, and μ_k is the mean signal value of all samples in the k window. The d_{kj} is defined as follows:

$$d_{kj} = |X_{kj} - \hat{X}_k| \tag{3}$$

where, X_{kj} is the sensor signal value of the j-th sample from the k-th window, $\hat{X}_k$ is a median sensor sample value in the k-th window.

B. AUTOCORRELATION FEATURES

One of the most important similarity measures is the self-similarity computed from the autocorrelation function (ACF) of sensor signals at different time lags. A sudden change in sensor signal results in increasing the correlation between successive signal parts since the regular signal sensor oscillates like a white noise whose correlation function oscillates and intersects the zero axes very fast. This means that the area under the ACF increases with the occurrence of a novel event. Suppose we have a sequence of sensor samples X_i, the ACF is computed at the lag τ as follows:

$$R(\tau) = \frac{\sum_{i=1}^{N-\tau} (X_i - \mu_N)(X_{i+\tau} - \mu_N)}{\sum_{i=1}^{N} (X_i - \mu_N)^2} \tag{4}$$

where N is the total number of samples and μ_N is the mean value over all samples. Other important features which could be extracted from the ACF are the skewness, kurtosis, and sum of correlation values at different lags.

$$Kurtosis = \frac{1}{T} \frac{\sum_{\tau=1}^{T} (R(\tau) - \mu_r)^4}{\sigma_r^4} \tag{5}$$

$$Skewness = \frac{1}{T} \frac{\sum_{\tau=1}^{T} (R(\tau) - \mu_r)^3}{\sigma_r^3} \tag{6}$$

$$ACF_{sum} = \sum_{\tau=1}^{T} R(\tau) \tag{7}$$

where μ_r, σ_r is the mean and standard deviation of the $R(\tau)$ values. The features extracted from the ACF reflect the self-similarity of different signal parts.

C. OTHER STATISTICAL FEATURES

Another set of statistical features is also extracted based on entropy, the coefficient of variation and minimum ratio. The

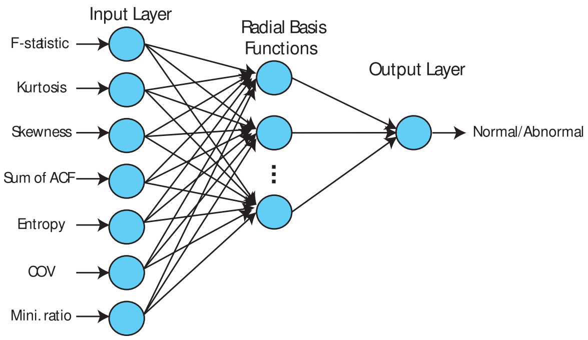

FIGURE 4. An example of a neural network architecture.

Entropy measures the degree of uncertainty of the sensor samples. The assumption is the normal signals have less uncertainty than the novelty signal. The Entropy H is defined as:

$$H(X) = -\sum_{i=1}^{N} P(X_i) \log P(X_i) \tag{8}$$

where, $X_i = \{x_1, x_2, \ldots, x_N\}$ is a set of random phenomena, and $P(X_i)$ is a probability of the sensor reading X_i. A novel event represents new information, which results in increased Entropy values. A sudden signal change meant more entropy.

Coefficient of variation (COV) is measuring the dispersion of sensor samples:

$$COV = \frac{\sigma}{\mu} * 100 \tag{9}$$

Minimum ratio (MR) is another feature, which reflects the similarity of two successive sensor signal windows $X1$ and $X2$:

$$MR = \frac{1}{n} \sum_{i=1}^{n} \min\left(\frac{X1_i}{X2_i}, \frac{X2_i}{X1_i}\right) \tag{10}$$

A sudden signal change due to a novel event results in decreasing the minimum ratio. If the two successive windows are identical as a result of a normal event, the minimum ratio is approximately equal to 1.

V. FEED-FORWARD NEURAL NETWORKS

The feed-forward neural network is one of the powerful classifiers that processes the input data across a series of connected layers where connections between the neurons do not form a cycle. The input layer forwards the d-dimensional feature vector, $\mathbf{x}$, to the hidden layer. Each neuron in the hidden layer is computing an activation function σ (e.g. hyperbolic tangent) over the sum of input features multiplied by a set of weights $\mathbf{W}$ plus bias term b.

$$h(\mathbf{x}) = \sigma(\mathbf{W}^T \mathbf{x} + b), \tag{11}$$

The network output is a linear weighted sum of the hidden units connected to the output layer. Figure 4 shows the architecture of a single hidden layer feed-forward neural network (FFNN) where the input feature vector is computed as described in the previous section.

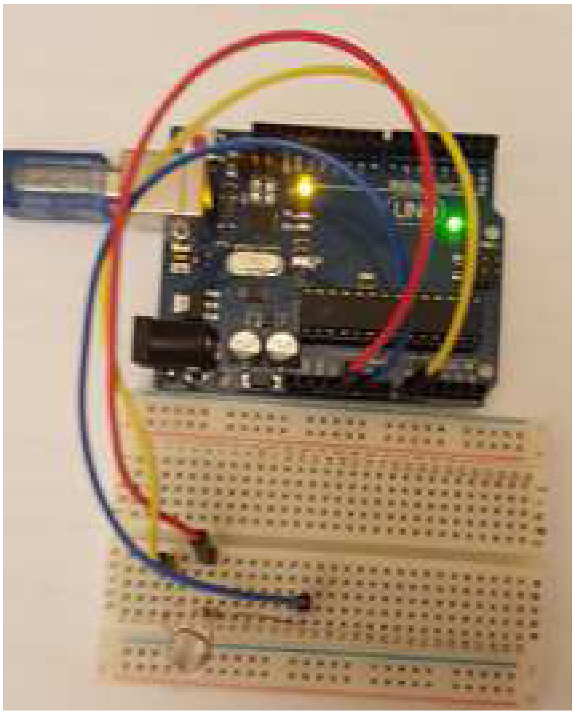

FIGURE 5. Sensor data acquisition system.

VI. RESULTS AND DISCUSSION

A. DATASET AND EVALUATION

The proposed method is evaluated on two dataset sets. The first one is collected in real-time by using Arduino Uno microcontroller board, and light sensor to detect novelties in light sensor signals and the second is the occupancy dataset [17] collected from 4 different sensors; light, temperature, CO_2, and humidity sensors in order to predict the occupancy of an office room.

Figure 5, shows the experimental setup used for sensor data acquisition, which consists of an Arduino Uno microcontroller board, and light sensor. The novelty detection approach discussed in this paper is applied to successive sensor data windows to detect any novelty, which might result from sensor data change in a smart home, due to any activity or for other reasons.

Six performance metrics [18], [19] are used to evaluate the event detection system performance. Table 1 shows the confusion matrix for our problem, where TP and TN represent the number of abnormal and normal signals that are classified correctly, and FN and FP represent the number of abnormal and normal signals that are misclassified. Sensitivity (Sens.) measures the rate of abnormal events. Specificity (Spec.) measures the proportion of normal sensor signals that are correctly identified. Sensitivity, therefore, assess the avoiding of false normal events, and similarity, specificity evaluates the avoiding of false abnormal events (novelties). Accuracy (Acc.) measures the population of the correctly predicted novelties. The F1-score (F1-sc.) is the harmonic mean of precision (Prec.) and sensitivity. The G-mean is computed by

TABLE 1. Confusion matrix for an event detection problem.

	Predicted Abnormal Signal	Predicted Normal Signal
Abnormal Signal	TP (True positive)	FN (False negative)
Normal Signal	FP (False positive	TN (True negative)

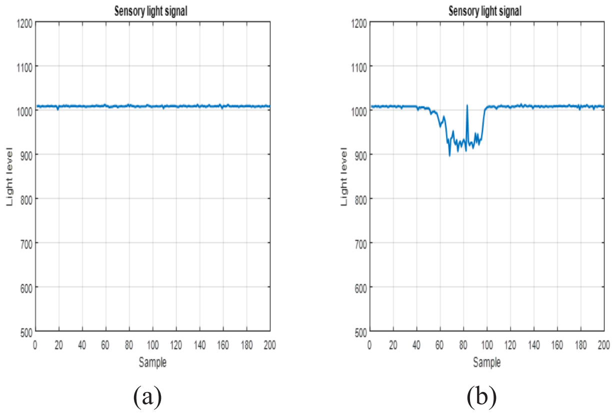

FIGURE 6. Example of a light signal. (a) Normal light signal (no novelty). (b) Abnormal light signal (as a result of novelty).

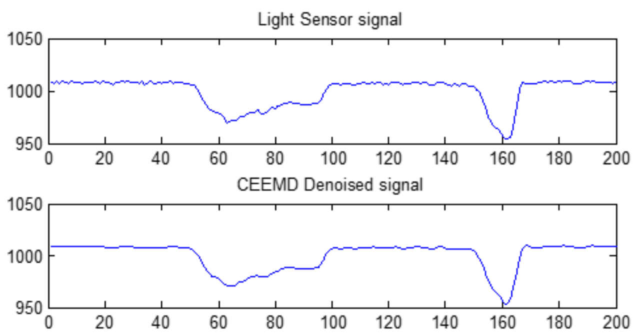

FIGURE 7. EMD filtered light sensor signal.

TABLE 2. Classifier performance metrics.

Metric	Formula	FFNN (%)	LVQ (%)
Sensitivity	$\frac{TP}{(TP+FN)}$	100	90.0
Specificity	$\frac{TN}{(FP+TN)}$	100	100
Precision	$\frac{TP}{(TP+FP)}$	100	80.0
Accuracy	$\frac{(TP+TN)}{(TP+TN+FP+FN)}$	100	83.3
F1-score	$\frac{2TP}{(2TP+FP+FN)}$	100	90.9
G-mean	$\sqrt{Sensitivity + Specificity}$	100	89.4

TABLE 3. Performance evaluation of the occupancy's testing set$_1$.

Sensor	Classifier	Sens.	Spec.	Prec.	Acc.	F1-sc.	G-mean
Light	KNN	92.98	100.00	100.00	96.88	96.36	96.42
	DT	89.47	100.00	100.00	95.32	94.44	94.59
	RF	92.28	100.00	100.00	96.57	95.98	96.06
	FFNN	96.49	100.00	100.00	98.44	98.21	98.22
Temp.	KNN	54.21	74.68	63.12	65.58	58.32	63.62
	DT	62.10	69.28	61.78	66.09	61.94	65.59
	RF	67.80	67.11	62.23	67.42	64.90	67.45
	FFNN	69.82	93.12	89.03	82.77	78.26	80.63
CO_2	KNN	94.12	53.71	61.91	71.66	74.69	71.10
	DT	90.35	57.15	62.76	71.90	74.07	71.85
	RF	94.91	58.83	64.82	74.86	77.03	74.72
	FFNN	97.71	78.05	78.06	86.78	86.79	87.33
Humidity	KNN	89.21	95.93	94.60	92.94	91.82	92.51
	DT	86.75	94.03	92.08	90.80	89.34	90.32
	RF	96.05	97.40	96.73	96.80	96.39	96.72
	FFNN	93.33	98.66	98.24	96.29	95.72	95.96

taking the square of the accuracy on both classes. A higher Gmean value means that the method performs well on both classes.

B. REAL-TIME LIGHT SENSOR

To test the validity of the proposed approach in testing novelties in sensor signals, twenty cases have been studied with ten normal cases and other cases with novelties. Figure 6 shows an example of the acquired light signals in the two scenarios (i.e. normal and abnormal). To eliminate noise effect before extracting the features, EMD is used to filter the signal from high-frequency noise as shown in Figure 7. An example of the extracted features for 10 normal sensor signals and 10 signals with novelties is shown in Figures 8. There is a clear difference between the features of normal and abnormal cases. For example, Figure 8 (f) shows the variation of the F-statistic of Levene's test among different test cases. The values for the first normal test cases are much lower than the values of the next 10 cases which encompassed a novelty.

We compare two popular neural network algorithms; Feed-Forward Neural Network (FFNN) and Learning Vector Quantization (LVQ) neural networks as shown in Table 2. The FFNN has been trained with 50 hidden units using Gradient descent with momentum and adaptive learning rate backpropagation algorithm. Testing the FFNN classifier resulted in a 100% for all of the 6 metrics in contrary to the LVQ classifier.

C. OCCUPANCY DETECTION

The dataset is divided into three sets; training set, testing set$_1$ collected with the office door closed and testing set$_2$ collected with the office door opened. The total number of samples acquired simultaneously from the 4 sensors for training is 8143, and 2665 for the testing set$_1$, and 9752 for the testing set$_2$. In order to evaluate the proposed method, the data is divided into a number of overlapping windows. If the occupancy (i.e. the event) is detected, the window is classified as a novel signal otherwise as a normal signal. Here, the window size is set to 100 samples.

Tables 3 and 4 show comparison results of 4 different classifiers on both testing set$_1$ and set$_2$ of 4 different sensors. We compare k-nearest neighbor (KNN), decision tree (DT), random forests (RF), and feed-forward neural network (FFNN). For KNN, the number of neighbors k is set to 10. For RF, the total number of trees is 500. The FFNN classifier has a single hidden layer with 50 hidden units.

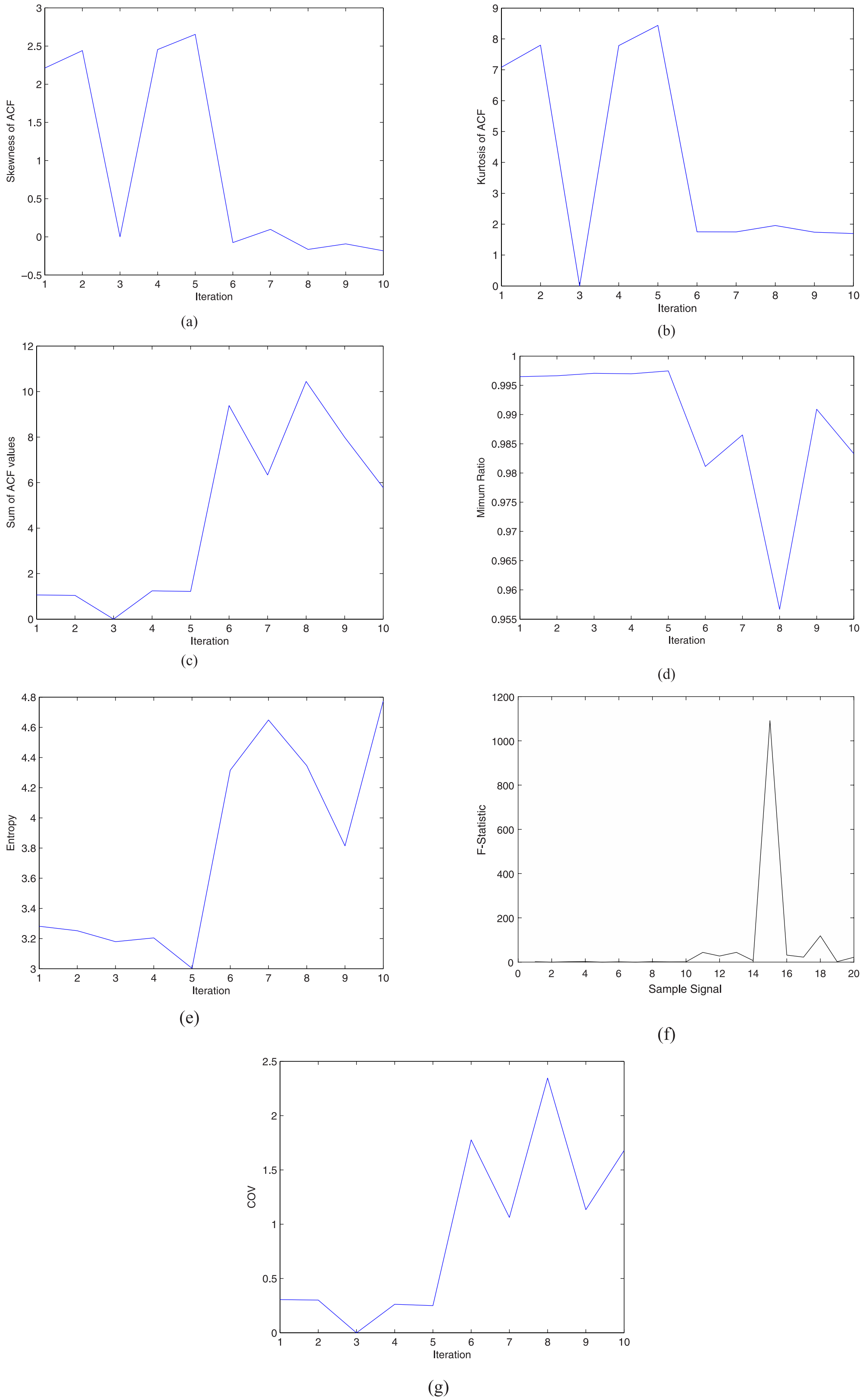

FIGURE 8. **Example of extracted features for 10 normal sensor signals and 10 signals with novelties. (a) Skewness of the ACF. (b) Kurtosis of the ACF. (c) Area under the ACF. (d) Minimum Ratio. (e) Entropy. (f) F-Statistic of LT. (g) Coefficient of Variation.**

TABLE 4. Performance evaluation of the occupancy's testing set_2.

Sensor	Classifier	Sens.	Spec.	Prec.	Acc.	F1-sc.	G-mean
Light	KNN	86.50	93.30	83.66	91.37	85.06	89.83
	DT	83.51	96.44	90.29	92.76	86.77	89.74
	RF	87.85	96.71	91.38	94.19	89.58	92.17
	FFNN	89.05	95.65	89.05	93.78	89.05	92.30
Temp.	KNN	73.70	80.24	59.68	78.39	65.95	76.90
	DT	60.61	77.19	51.32	72.48	55.58	68.40
	RF	72.61	81.47	60.86	78.95	66.22	76.91
	FFNN	80.63	80.19	61.75	80.31	69.94	80.41
CO_2	KNN	83.88	81.00	63.65	81.81	72.38	82.42
	DT	79.75	83.79	66.13	82.64	72.30	81.75
	RF	84.75	82.27	65.48	82.97	73.88	83.50
	FFNN	75.45	90.60	76.12	86.30	75.78	82.68
Humidity	KNN	76.98	66.64	47.80	69.58	58.98	71.63
	DT	72.97	62.91	43.84	65.77	54.77	67.75
	RF	77.42	65.80	47.32	69.10	58.74	71.38
	FFNN	72.17	84.50	64.88	81.00	68.33	78.09

For the testing set_1, the light sensor gives the best result with F1-score (%) of the FFNN is 98.21, while for the RF is 95.98, DT is 94.44, and KNN gives 96.36. The second best sensor for detecting the occupancy is the humidity. F1-score (%) of the FFNN is 95.72, while for the RF is 96.39, DT is 89.34, and KNN gives 91.82. In general, the FFNN classifier gives better performance than the other classifiers, except in one case (i.e. humidity sensor) the RF can outperform the FFNN. The results show that the proposed method can perform well on different sensor types.

For the testing set_2, the results are slightly deteriorated due to the changing of the environment of acquiring data. The light sensor gives the best result, then the CO_2 sensor. For the light sensor, the FFNN's F1-score is 89.05%, while for the RF, DT, and KNN, the F1-score is 89.58%, 86.77%, and 85.06% respectively. The the CO_2 sensor is the second best sensor for detecting the occupancy, and the humidity moved to the third place. The CO_2's F1-score of the FFNN, RF, DT, and KNN is 75.78%, 73.88%, 72.30% and 72.38% respectively. Still, the FFNN classifier generally gives better performance than the other classifiers. The results show that a good setup of the sensors in the testing environment would help to increase the system performance.

VII. CONCLUSIONS

This paper presents a new approach for novelty detection in sensor signals based on Levene's test which tests the homogeneity of variances of samples taken from the same population and combined with other statistical and autocorrelation features. The proposed system tested on four different types of sensors (light, temperature, CO_2 and humidity) for occupancy detection. For the light sensor, novelty detection accuracy reached 98.44% while both sensitivity and precision reached 96.49% and 100.00% respectively on the testing set_1 for occupancy detection. These performance indicators show the effectiveness of the extracted features for novelty detection in sensor signals. This helps in processing sensor signal at the Fog level resulting in faster and efficient knowledge transfer to the cloud saving both the cost of data transfer and storage on the cloud. Different types of low computational classifiers have been examined. In most cases, the neural network outperforms the other classifiers. Avoiding the problem of parameter selection and the thresholding process are major advantages of this approach. Future research will focus on the addition of more features to increase the system reliability in an unconstrained environment.

REFERENCES

[1] (2015). *SIM900 GPRS/GSM Shield*. Accessed: Apr. 2, 2017. [Online]. Available: http://linksprite.com/wiki/index.php5?title=SIM900_GPRS/GSM_Shield

[2] E. I. Gaura, J. Brusey, M. Allen, R. Wilkins, D. Goldsmith, and R. Rednic, "Edge mining the Internet of Things," *IEEE Sensors J.*, vol. 13, no. 10, pp. 3816–3825, Oct. 2013.

[3] A. Jain, E. Chang, and Y.-F. Wang, "Adaptive stream resource management using Kalman filters," in *Proc. ACM Int. Conf. Manage. Data (SIGMOD)*, 2014, pp. 11–22.

[4] D. Chu, A. Deshpande, J. M. Hellerstein, and W. Hong, "Approximate data collection in sensor networks using probabilistic models," in *Proc. 22nd Int. Conf. Data Eng.*, Apr. 2006, pp. 48.

[5] D. Goldsmith and J. Brusey, "The spanish inquisition protocol—Model based transmission reduction for wireless sensor networks," in *Proc. IEEE Sensors*, Nov. 2010, pp. 2043–2048.

[6] D. Tulone and S. Madden, "PAQ: Time series forecasting for approximate query answering in sensor networks," in *Wireless Sensor Networks*. Berlin, Germany: Springer, 2006, pp. 21–37.

[7] D. Tulone and S. Madden, "An energy-efficient querying framework in sensor networks for detecting node similarities," in *proc. 9th Int. ACM Symp. Modeling, Anal. Simulation Wireless Mobile Syst. (MSWIM)*, 2006, pp. 291–300.

[8] U. Raza, A. Camerra, A. L. Murphy, T. Palpanas, and G. P. Picco, "What does model-driven data acquisition really achieve in wireless sensor networks?" in *Proc. IEEE Int. Conf. Pervasive Comput. Commun.*, Mar. 2012, pp. 85–94.

[9] J. Brusey, R. Rednic, E. I. Gaura, J. Kemp, and N. Poole, "Postural activity monitoring for increasing safety in bomb disposal missions," *Meas. Sci. Technol.*, vol. 20, no. 7, p. 075204, 2009.

[10] O. Ojetola, E. I. Gaura, and J. Brusey, "Fall detection with wearable sensors–safe (smart fall detection)," in *Proc. 7th Int. Conf. Intell. Environ.*, Jul. 2011, pp. 318–321.

[11] S. K. Ghosh, M. Suman, R. Datta, and P. K. Biswas, "Power efficient event detection scheme in wireless sensor networks for railway bridge health monitoring system," in *Proc. IEEE Int. Conf. Adv. Netw. Telecommun. Syst. (ANTS)*, Dec. 2014, pp. 1–6.

[12] L. Yu, N. Wang, and X. Meng, "Real-time forest fire detection with wireless sensor networks," in *Proc. Int. Conf. Wireless Commun., Netw. Mobile Comput.*, Sep. 2005, pp. 1214–1217.

[13] E. I. Gaura, J. Brusey, and R. Wilkins, "Bare necessities—Knowledge-driven WSN design," in *Proc. IEEE SENSORS*, Oct. 2011, pp. 66–70.

[14] D. P. Mandic, N. U. Rehman, Z. Wu, and N. E. Huang, "Empirical mode decomposition-based time-frequency analysis of multivariate signals: The power of adaptive data analysis," *IEEE Signal Process. Mag.*, vol. 30, no. 6, pp. 74–86, Nov. 2013.

[15] M. A. Colominas, G. Schlotthauer, and M. E. Torres, "Improved complete ensemble EMD: A suitable tool for biomedical signal processing," *Biomed. Signal Process. Control*, vol. 14, pp. 19–29, Nov. 2014.

[16] H. M. Raafat and A. S. Tolba, "Homoscedasticity for defect detection in homogeneous flat surface products," *Textile Res. J.*, vol. 85, no. 8, pp. 850–866, 2015.

[17] L. M. Candanedo and V. Feldheim, "Accurate occupancy detection of an office room from light, temperature, humidity and CO_2 measurements using statistical learning models," *Energy Buildings*, vol. 112, pp. 28–39, Jan. 2016.

[18] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognit. Lett.*, vol. 27, no. 8, pp. 861–874, 2006.

[19] D. M. W. Powers, "Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation," *J. Mach. Learn. Technol.*, vol. 2, no. 1, pp. 37–63, 2011.

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