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Early Warning of Ship Fires Using Bayesian Probability Estimation Model

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Abstract—

Economic pressure to reduce the cost of the U.S. Navy ships has brought into the focus the need to significantly reduce the size of a ship's crew. In order for an automated system to replace humans while making critical decisions, it is required that such a system be able to accurately predict future events. This paper presents a wavelet theory based prediction system to predict the occurrences of ship's fires. Furthermore, while the prediction model predicts the future events, the accuracy of prediction has to be quantified by formulating a probability index that will mirror the confidence on the prediction. As such, a Bayesian theory based probability estimation model (BPEM) is developed for estimating the probability that the predicted values are within specified limits of tolerance. Tests with the U.S Naval Research Laboratory (NRL) data, covering various fire scenarios, validate that the proposed methodology consistently provides earlier detection as compared to the published results from the NRL' early warning fire detection system (EWFD) system.

I. Introduction

EVER increasing risks of terror attacks, along with global economic situations have resulted in accelerated efforts to replace human manpower by automated systems. Such systems will be deployed to provide real-time monitoring and control of locations that are highly vulnerable to damages and attacks.

In order to address such challenges, the United States Navy has constituted a program called Damage Control Automation for Reduce Manning (DC-ARM) [1]. The DC-ARM program, sponsored by the United States Office of Naval Research, is dedicated towards enhancing automation of a ship's damage control system. The primary objective of the DC-ARM program is to develop highly technical and advanced systems that can augment or perhaps replace actions and decisions made by a ship's crew. Desirable features of such an automated system include early warning and detection of fires on board ships, and an ability to discriminate between an actual (fire) event and a false alarm (nuisance) event.

One of the results of the DC-ARM program is the development of an Early Warning Fire Detection (EWFD) system [2], which is a multi-criteria based fire detection system. In the EWFD system, an array of sensors feed raw data into a probabilistic neural network, which then predicts the probability associated with the occurrence of an actual fire event [3]. A database of fire classification models is developed by gathering data from different types of fires and nuisance events. Incoming data from the sensors is analyzed against such fire classification models and probabilistic neural network is used to predict the probability of any fire event [4]. The output of this algorithm was the probability that a fire event existed. A warming was issued when the probability reached a value of 0.75. The alarm state was triggered if the probability was greater than 0.85 for three of more consecutive predictions [1]-[2].

Early and reliable detection of any abnormal event is not only desirable but highly crucial, and more so, in the case when there is a fire on a ship. With this objective, this paper presents a novel method for accurate prediction, and reliable estimation of the probability associated with predicting abnormal events (such as fires) on ships. Specifically, a wavelet-based multi-scale formulation is developed to predict future values of any system that is being monitored. In conjunction with the wavelet prediction model, a Bayesian theory based probability estimation model (BPEM) is developed to assign the probability associated with each of the predicted values.

Published results demonstrate that the EWFD formulation outperforms commercial fire detection system in terms of improving detection rates, providing faster response times to fire, and reducing false alarms [1]-[2]. In this paper, the EWFD formulation is compared with the proposed wavelet-Bayesian theory approach. The proposed approach consistently provides faster and reliable detection of fires as compared with the EWFD method.

In what follows, an introduction to the wavelet-based multi-scale prediction model is outlined. Next, the proposed Bayesian-theory based probability approach is presented. Finally, to demonstrate the proposed strategy, the results from the wavelet-Bayesian theory approach are compared with the EWFD method.

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II. BACKGROUND

A practical challenge associated with any prediction model is that there is always a chance that the prediction may not turn out to be true. Therefore, merely predicting the occurrence of an abnormal event is not enough; it is desirable to formulate a probability that will mirror the confidence on the accuracy of the prediction.

Studies based on specific data distribution for several processes have shown that prediction models for those processes can provide the theoretical confidence interval for estimation. As an example, [5] used the evaluation of a T^2 statistic as a reality check for deciding if the future predictions are reliable and thus can be used for making control decisions. Likewise, [6] used different degrees of prediction to convey the uncertainty in the weather forecast.

The limitation of using confidence interval is that it does not describe the possibility that the prediction will actually equal the real future value. It merely shows the statistical accuracy of the prediction. It is well known that a Bayesian probability approach provides a statistical calculation based framework for determining the likelihood, which is dependent on prior knowledge, accumulated experience, and empirical data [7]-[8]. The simple formulation of Bayesian probability approach is,

$$\text{Posterior} \propto (\text{Prior} \times \text{Likelihood Function}) \tag{1}$$

where, Posterior is the probability for the expected event, Likelihood function is the estimated probability derived from normal operation data, and Prior is the inferred specified current belief provided by all currently available information. By definition, Prior is used to incorporate the effects of new data, and information of any recent process changes. Therefore, Bayesian probability approach can adjust the confidence of prediction by adopting a two-fold approach: it revises the prediction once future data is available (Likelihood function), and it factors in influence of external changes (Prior).

Several research areas have benefited from the application of a Bayesian probability approach. In statistical process monitoring, [9] combined Bayesian probability approach with principle component analysis (PCA), and compared the results with other types of PCA. In biomedical research, [10] used Bayesian theory to determine the optimal parameters of an HIV infection model.

III. THEORETICAL FORMULATION

Development of the probability of prediction consists of three parts: In part one, actual data from NRL experiments in EWFD and DC-ARM are used to develop the wavelet-based multi-scale prediction model (Fig. 1.). In part two, Bayesian theory is used to calculate deviation of posterior from deviation of history data and prior data (Fig. 2.). Finally, the calculation of the probability from deviation of posterior and normal probability distribution (Fig. 3.) is performed in part three.

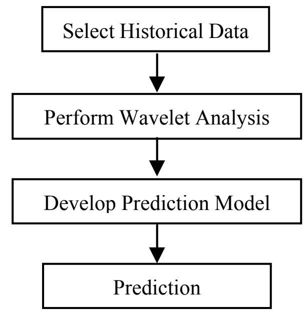

Fig.1. Procedure to develop the wavelet prediction model

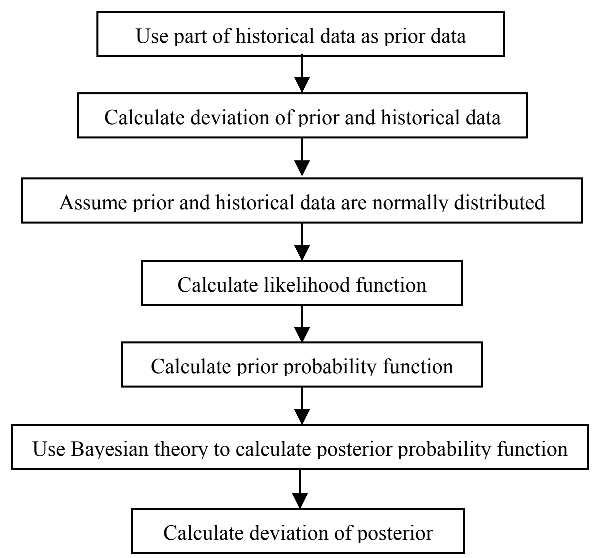

Fig.2. Procedure to calculate deviation of posterior

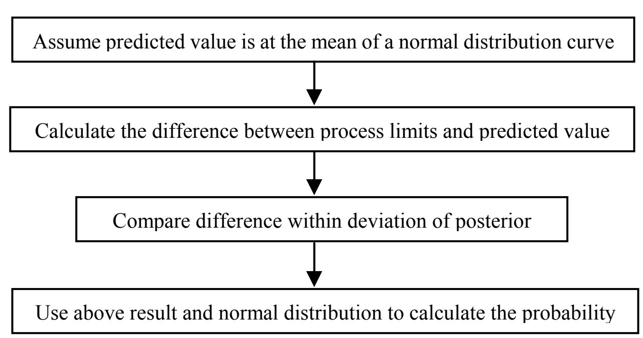

Fig.3. Procedure to calculate probability

III.1 WAVELET-BASED PREDICTION MODEL

Fire generation and propagation is essentially a process that operates at different scales; from slow, time-varying behavior (such as, rate of smoke detection, sensor drifts, changes due to mist system operation), to rapid changes (such as, rate of spreading of fire and generation of smoke). To cite a common example, the rate of smoke generation from an oil fire will be much higher than the rate of smoke generation from the burning of paper. Likewise, the rate at which fire spreads in a room filled with paper will be faster than it spreads in a room filled with resin plastic.

The success of wavelet-based approaches in extracting features of interest at different scales, ([11]-[12]), inspires this research to use a wavelet-based multi-scale prediction model for predicting values of generation and propagation of fire. In this research, time-series sensor data from the EWFD and DC-ARM tests was used as input to the wavelet-based multi-scale prediction. The prediction model was trained using normal data (without any fire event). Wavelet analysis was used to decompose the data into wavelet approximations and details at the specified level of decomposition. The determination of the mother wavelet and the level of decomposition are user specific parameters, and are dependent on the data features that the user wishes to extract and analyze. Wavelet approximations and details at the higher levels of decomposition were combined per the mathematical model developed in [13] to formulate predictions for the future values of the time-series data. The Root Mean Square Error (RMSE) and Local Point Error (LPE) between the data predicted from the model and the actual (real-time) value of the predicted data were used as metrics to fine-tune the model coefficient. Once the model was optimized, the model was then used for making real-time predictions. The specifics of the wavelet prediction model are presented in [13].

III.2 BAYESIAN PROBABILITY ESTIMATION MODEL

It is assumed that the process data can be approximated to distribute normally. An important feature of the proposed methodology is that the predicted value is assumed to be at the mean of a normally distributed curve. The underlying principle is that the probability of prediction is inversely related to the difference between the predicted and actual value; if the difference is low, then the probability is high. The principle is applied for the case when the probability of prediction is a direct measure of the confidence that estimated value lies within some certain pre-determined process limits. Principles of continuous probability distribution and a recursively updated Bayesian probability estimation model are used to derive a formulation for the probability associated with the future predicted value. Details of the proposed formulation are derived in [14].

Mathematically, the derivation of the probability consists of the following steps: first, historical data, under normal operation, is used to calculate the deviation ($\sigma_{history}$). Then, data representative of the recent history of the process (Prior data) is used to calculate the deviation of the Prior (σ_{Prior}). The deviation of the posterior is inferred from [15] as follows:

$$\frac{1}{\sigma^2_{posterior}} = \frac{1}{\sigma^2_{prior}} + \frac{1}{\sigma^2_{history}} \tag{2}$$

The process limits play a critical role in determining the probability. Before calculating the probability, the process limits need to be determined. It is important to highlight that the term probability is used to determine the possibility of real data falling outside of the process limits. Since the historical and Prior data is assumed to be approximately normally distributed, the estimation can be assumed to be approximately normally distributed. Besides, the estimation value is assumed to be at the mean of a normal distribution. Therefore, based on the characters of normal distribution [16], the probability can be calculated from the difference between the mean of distribution and a certain limit and deviation of data distribution. However, in Bayesian probability estimation model, the deviation of posterior will replace the deviation of data distribution to calculate the probability.

Per the definition of normal distribution, the probability between mean of data +/- one (1) deviation will be approximate 68.26%. As such, the first step in determining the probability is to calculate the difference between mean and process limits, and then to calculate the ratio Z, as given by,

$$Z = \frac{X - \mu}{\sigma} \tag{3}$$

where, X is process limit, and μ is the mean of predicted value.

Finally, the probability can be calculated by integrating normal distribution formulation as follows

$$\text{Probability}(z_1 < Z < z_2) = \frac{1}{\sqrt{2\pi}} \int_{z_1}^{z_2} \exp\left(\frac{-z^2}{2}\right) dz \tag{4}$$

IV. RESULT

Haar wavelets [17] were used to develop the wavelet prediction model. Three (3) levels of wavelet decomposition, along with the model coefficient α=2.0 were used as optimized parameters for the wavelet model. Due to the nature of the types of fires (listed below), the sensor data did not contain significant contributions from events at multiple scales; therefore, three (3) levels of wavelet decomposition were adequate to capture the dynamics of the process.

For recursive BPEM, prior and likelihood data both used a moving window of fixed size for data collection. Historical data of 1000 data points was used as the likelihood function data, and the most recent 150 data points from the historical data were used as the prior data. The pre-determined process limits was calculated to be the average of the historical data plus three times deviation of the historical data.

The test data are from EWFD demonstration in 2000 [2] and DC-ARM final demonstration [1]. Historical data was used to train and optimize the wavelet prediction model, and prior data was used as the raw data input to the optimized the wavelet prediction model.

The first data set, EWFD_127, was set up to simulate real fire caused by pipe insulation and fuel oil flaming in chief petty officer living room. Figure 5(A) compares the values predicted from the wavelet prediction model to the actual real-time values from an ionization sensor. The plots are practically indistinguishable; as such, the wavelet prediction model is a good reflection of the process data trend. The fire started around sampling time=100, and the EWFD system issued a warning at sampling time=215 of a 75% change of a real fire event. In contrast, the BPEM issued the 75% probability warning at sampling time=143 (Figure 5(A)).

The second data is from EWFD_128 test, which was set up to simulate real fire caused by smoldering bedding material in Tomahawk equipment room using two heat source. Figure 6(A) shows that the predictions from the wavelet model closely followed the actual real-time values from a carbon monoxide sensor. The fire started around sampling time=100, and the EWFD system issued a warning at sampling time=337. The warning from BPEM was issued at sampling time=260 (Figure 6(B)).

The final data is from EWFD_132, which was set up to simulate real fire caused by smoldering oily rag, newspaper, cardboard in a 55 gallon drum using two heat source in an operating office. Figure 7(A) shows that the real-time ionization sensor values were closely mirrored by the predictions from the wavelet model. The fire started around sampling time=75, and the EWFD system issued a warning around sampling time=350, whereas the BPEM issued a first warning at sampling time=153 and then a final, recurring warning at sampling time=194 (Figure 7(B)).

In case of fire events, an early warning and detection is critical to trigger off damage control system on the ships. The proposed system was able to accurately predict the sensor response for fire events, and importantly, it reliably estimated probabilities associated with such predictions. The estimated probabilities were instrumental in providing a significantly early warning of fire as compared to the currently implemented EWFD system.

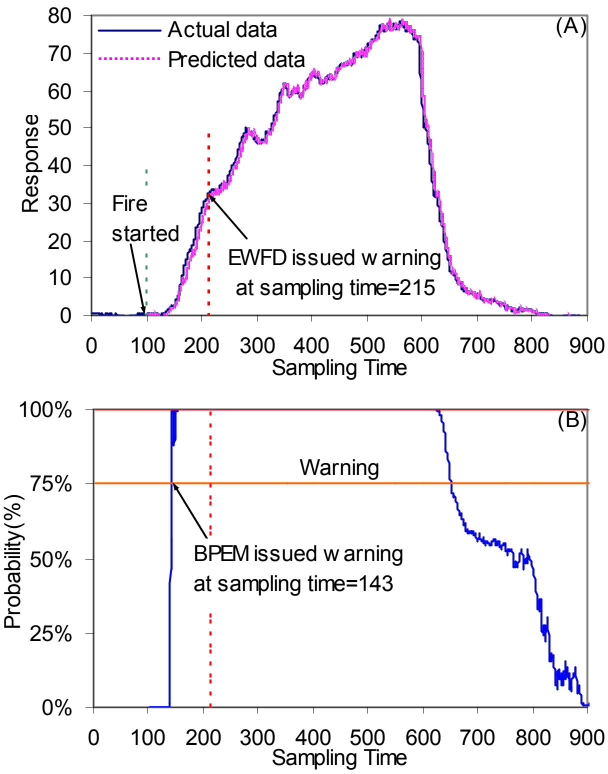

Fig. 5. (A) EWFD_127 actual real-time data and predicted data from wavelet prediction model; (B) Probability estimation from BPEM

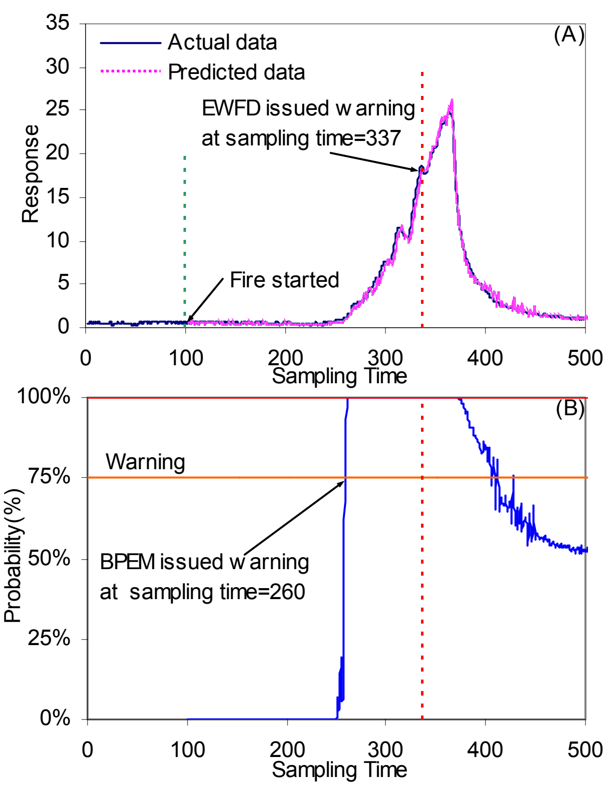

Fig. 6. (A) EWFD_128 actual real-time data and predicted data from wavelet prediction model; (B) Probability estimation from BPEM

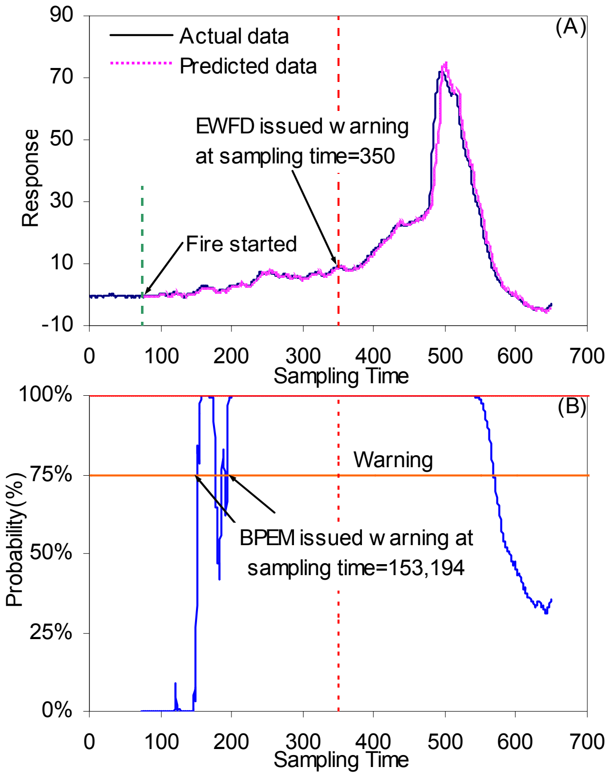

Fig. 7. (A) EWFD_132 actual real-time data and predicted data from wavelet prediction model; (B) Probability estimation BPEM

V. Conclusion

A wavelet-based multi-scale model was successfully used to predict values of future data points. The property of the Bayesian probability estimation model effectively combined the effects of recent history (Prior) and the empirical influence of historical data (Likelihood function). Such a formulation consistently and reliably detected fire events about an average of 100 time steps earlier than EWFD system.

Future directions in this work include modification of the Bayesian probability estimation model to include immunity to nuisance alarms. Additionally, it will be interesting to study the sensitivity of process limits to the estimation of probability.

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