Fault detection for salinity sensors in the Columbia estuary

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[1] Sensors deployed in the Columbia River estuary gather information on physical dynamics and changes in estuary habitat. Of these sensors, conductivity sensors are particularly susceptible to biofouling, which gradually degrades sensor response and corrupts critical data. Several weeks may pass before degradation is visibly detected. Since the onset time of biofouling is unknown, an indeterminate amount of measurement data is corrupted. To speed detection and minimize data loss, we develop automatic biofouling detectors based on machine learning approaches for these conductivity sensors. We demonstrate that our detectors identify biofouling at least as reliably as human experts. In addition, these detectors provide accurate estimates of biofouling onset time. Real-time detectors installed during the summer of 2001 produced no false alarms yet detected all episodes of sensor degradation before the field staff. INDEX TERMS: 1894 Hydrology: Instruments and techniques; 4894 Oceanography: Biological and Chemical: Instruments and techniques; KEYWORDS: fault detection, biofouling, sensor degradation, novelty detection, sensor failure, salinity measurement


1. Biofouling Problem

[2] Environmental observation and forecasting systems (EOFS) gather, process, and deliver environmental information to facilitate sustainable development of natural resources. Our work is part of a pilot EOFS system being developed for the Columbia River estuary (CORIE) [Baptista, 2002; Steere et al., 2000; Baptista et al., 1999]. This system uses data from sensors deployed throughout the estuary (Figure 1) to calibrate and verify numerical models of circulation and material transport. CORIE scientists use these models to predict and evaluate the effects of development on the estuary environment [U.S. Army Corps of Engineers, 2001].

[3] CORIE salinity sensors deployed in the harsh estuary environment lose several months of data every year due to sensor degradation. As an example of the severity of the problem, degradation of salinity sensors is so common in late summer that the data archive contains little or no reliable salinity data for the beginning of the rainy season. Corrupted and missing field measurements compromise model calibration and verification. This in turn can lead to invalid environmental forecasts and erroneous conclusions about effects of development on the estuary environment.

[4] A common yet particularly insidious form of salinity sensor degradation is biofouling. Biofouling occurs when biological matter accumulates on the sensors, reducing their responsiveness. Field staff do not have time to study the sensor measurements every day searching for this gradual degradation. Consequently, the biofouling process goes undetected for weeks or months until a sensor becomes substantially compromised. Even after sensor failure is visually obvious, the precise onset time of biofouling remains uncertain, leaving a history of unreliable measurements.

[5] Early biofouling detection is made difficult by the normal variability of salinity measurements. Tides cause the measurements to vary from river salinity to near ocean salinity twice a day. In addition, the patterns of salinity measurements are different for every station. For instance, sensors near the mouth of the estuary measure higher salinity at tidal flood than do sensors further up-river. Changes in weather and ocean condition cause additional variations in salinity. To complicate biofouling detection further, the biofouling signature also varies from episode to episode.

[6] To improve the integrity of CORIE system data, we have two objectives. First, we should detect biofouling quickly (within several diurnal cycles). This early detection will limit the use of corrupted data in real-time or online
applications. Second, we should estimate the onset time of biofouling. Having an estimate of onset time will guide the staff in removing corrupted measurements from the data archive. In this work, we concentrate on developing automatic classification systems to detect biofouling of conductivity sensors used to measure salinity.

2. Characterizing Sensor Biofouling

Salinity is a measure of the mass in grams of dissolved salts in one kilogram of water (g/kg) and is expressed as a dimensionless conductivity ratio using the practical salinity scale [Millero and Poisson, 1981]. The CORIE systems includes several inductive conductivity and temperature (CT) sensors manufactured by Falmouth Scientific (Digital OEM C-T). Salinity is determined from the electrical conductivity of the water with corrections for temperature and pressure (more information is given by Picard and Emery [1990]).

A CT sensor reports reduced salinity when it biofouls. The sensor measures the conductivity of a calibrated volume of water. Biological material accumulating on the sensor fills the measurement cavity, reducing the actual volume of water measured. Consequently, the reported salinity is lower than the true salinity. Once biofouling begins, degradation increases until biological material fills the cavity and then levels off. The degradation rate and final level differs for every biofouling incident.

The CT sensors are treated with a standard marine antifouling agent, Tri-Lux II from Coutaulds Coatings, which reduces, but does not prevent biofouling. We observe two types of biofouling in the estuary, hard-growth and soft-growth. Hard-growth biofouling is primarily caused by barnacles growing on the sensors. Barnacles are primarily found on sensors close to the ocean where maximum tidal salinity is high. It is characterized by linear degradation until the barnacles fill the sensor measurement cavity. Soft-growth biofouling is caused by plant material growing on and around the sensor. It is characterized by by slow linear degradation with occasional interruptions in the downtrend. In addition, the sensor response partially recovers in the winter months, presumably due to plant material die back. In either case, the time from onset to complete biofouling takes anywhere from 3 weeks to 5 months.

Figure 2 illustrates both tidal variations in salinity and the effect that biofouling has on these measurements. It contains salinity time series from two sensors mounted at the Red26 station, Figure 1. The upper trace, from midwater mounted sensor CT1460, contains only clean measurements. The lower trace, from river bed mounted sensor CT1448, contains both clean and biofouled measurements. The first half of the two time series are very similar, but beginning on September 28th, the salinity measurements diverge. The deeper sensor, CT1448, exhibits the degradation typical of hard-growth biofouling.

3. Data for Biofouling Detector Evaluation

Previously, no automatic classification system existed for detecting sensor biofouling. In our context, an automatic classifier distinguishes signals from clean and biofouled sensors. Prior to this work, biofouling was identified by visually examining the salinity time series. When the salinity was lower than expected for several weeks, the sensor was declared biofouled. Our field staff have other responsibilities that prevent the daily examination of the salinity time series. It is common to have delays of several weeks between biofouling onset and detection. To improve the integrity of the CORIE system and to free the staff for other tasks, we developed two automatic classifiers, based on sequential likelihood ratio tests, that provide early biofouling detection and onset time estimates. Before discussing these classifiers, we describe the data used in our evaluations.
biofouling and has the most consistent salinity measurements of all the estuary stations. The second sensor is mounted at Tansy Point, labelled “tansy” in Figure 1, and is subject to both hard-growth and soft-growth biofouling. This station is further up-river than Sand Island, so the salinity measurements show greater sensitivity to changes in tidal strength and river flow. The third sensor is mounted on the Astoria-Megler Bridge Pier 169, labelled “am169” in Figure 1. This sensor is subject to primarily soft-growth biofouling and shows substantial variation with the spring-neap tidal cycle. The greater variability in both salinity and biofouling behavior makes biofouling detection more challenging at Tansy Point and Astoria-Megler than at Sand Island.

We developed our real-time biofouling detectors using time series segments from the CORIE data archive. Biofouling is most prevalent during the summer period of May to mid-October, so we limit our evaluation to this time period. We have four time series segments for Sand Island, three segments for Tansy Point, and two segments for Astoria-Megler. Figure 3 contains example time series for these stations that exhibit degraded measurements due to biofouling. For all the sensor data used in our evaluation, biofouling was previously verified by removing and inspecting the sensor. Biofouling onset time is unknown, so we estimated it visually with the assistance of our field scientist.

3.2. Data Features

Our first task involved identifying candidate input features for the classifiers. A useful classification feature shows a large shift in value when the sensor is biofouled, but has low variability when the sensor is clean. Maximum diurnal (md) salinity, defined as the maximum salinity over two tidal periods, satisfies these criteria. When the sensor is clean, the md salinity stays close to some mean value, with occasional dips of several units on the practical salinity scale precipitated by changing ocean and river conditions. When the sensor biofouls, the md salinity gradually decreases to typically less than half its normal mean value, as seen in the Figure 3 examples. The rate of biofouling varies with each incident. Once biofouling begins, a sensor progresses from clean to fully degraded in 20 to 150 diurnal cycles.

The md salinity occurs near the tidal flood when the water depth is highest. Minima and maxima in the depth or pressure signal indicate the times of tidal ebb and flood, respectively. We use the time of the tidal ebbs to window the search for maximum diurnal salinity in order to provide robustness against variability in the length of the diurnal period. The times of tidal ebbs are determined by finding minima in the pressure signal. We then find the maximum salinity between the times of each pair of tidal ebbs; this is the tidal maximum salinity. One tide of each pair will be stronger, resulting in higher salinity values. The maximum diurnal salinity is the larger of each pair of tidal maximum salinities. Figure 4 illustrates feature extraction.

Classifiers that monitor salinity alone can not distinguish natural decreases in salinity from early biofouling. An example of a natural salinity decrease is apparent in the top plot of Figure 3, beginning on 26 July. In addition, the spring-neap tidal cycle causes normal periodic decreases in md salinity as shown in the bottom plot of Figure 3. Natural salinity decreases can be recognized by examining a correlated source of uncorrupted information, such as a nearby clean sensor or a sensor measuring a related value. Possible related values include water temperature, river flow, and water depth. In this work, we use measurements from the temperature sensor included with each conductivity sensor. The temperature sensor is not subject to biofouling, so these measurements provide a correlated and uncorrupted source of salinity information.
The salinity and temperature at a station are products of the same mixing process of ocean and river waters, so we expect that the values at tidal flood will be correlated. To show this, we assume a standard linear mixing of ocean and river waters. The measured salinity \( S_m \) and temperature \( T_m \) at a station are then linear functions of ocean values \( \{S_o, T_o\} \) and river values \( \{S_r, T_r\} \):

\[
S_m = \alpha(t)S_o + (1 - \alpha(t))S_r
\]

\[
T_m = \alpha(t)T_o + (1 - \alpha(t))T_r
\]

where \( \alpha(t) \) is the mixing coefficient at time \( t \) and river salinity \( S_r \) is close to zero. We focused our work on the late spring through summer period when biofouling is most prevalent. In this period the temperature is anticorrelated with salinity, \( T_o < T_r \). The estimated mixing coefficient

\[
\alpha(t) = \frac{T_r - T_m}{T_r - T_o}
\]

will be well correlated with salinity, \( S_m \approx \alpha S_o \). Figure 5 contains time series of salinity and the temperature based mixing coefficient from Tansy Point that show this correlation. We estimate the ocean temperature to be a \( T_o = 8^\circ C \), based on minimum temperatures seen at the outermost sensor station (Sand Island).

### 4. Sequential Likelihood Ratio Classifiers

Classic discriminatory classifiers, which incorporate separate models for healthy and fault data, have limited applicability to our biofouling detection problem. Developing discriminatory classifiers require many examples of biofouling onset, which are not available for most sensors. In addition, these methods typically operate on a single measurement at a time, yet biofouling is a progressive process. Human experts make biofouling judgments by watching the behavior of the salinity signal over several weeks. We expect that combining information from several sequential measurements will improve classifier accuracy. Finally, the only estimate of biofouling onset time provided by classic methods is the detection time. Since biofouling is a gradual process, the data before the biofouling detection point will be corrupted. A reliable estimate of biofouling onset time will aid the staff in deciding how much data is unreliable.

To address these issues, we introduce sequential likelihood ratio (SLR) tests. SLR tests combine several sequential measurements for every classification decision. They can be adapted to provide estimates of biofouling onset times. By defining a parameterized model of biofouling behavior, we can estimate the biofouling rate in real-time. Since we can then fit the fault model to the measurements under test, the classifier can be developed using only clean data examples.

#### 4.1. SLR Tests

Sequential likelihood ratio tests accrue information to improve classification confidence [Fukunaga, 1990]. The likelihood ratio for fault detection is the probability of a data measurement \( x \) assuming it is faulty, \( p(x|f) \), divided by the probability of \( x \) assuming it is clean, \( p(x|c) \). A likelihood ratio test compares the logarithm of this ratio to a threshold.

If the value is above the threshold, the data is declared faulty. A sequential likelihood ratio test sums the log likelihood ratios over some time window and compares the sum to a threshold, \( \lambda \), that is

\[
h = \sum_{n=1}^{N} \ln \frac{p(x_n|f)}{p(x_n|c)} \geq \lambda
\]

where the window begins at time \( n = \tau \) and ends at current time \( N \). The window start time \( \tau \) is the maximum likelihood estimate of biofouling onset [Basseville, 1988]. If most of the data is faulty (clean), the sum will lie well above (below) the threshold and we will have high confidence in the classification decision.

#### 4.2. Biofouling Fault Model

In order to develop a sequential likelihood ratio test for biofouling detection, we first define models of the clean and biofouled data. We start with the model for salinity alone and later add temperature. Maximum diurnal salinity \( s \) is modeled as a Gaussian signal with mean \( \mu_s \) and variance \( \sigma_s^2 \). When the sensor is clean, it measures the true salinity, \( s_n = s \). When the sensor biofouls, the measured value is suppressed relative to the true salinity. We model the initial salinity suppression as a linear downtrend with rate \( \rho \), that begins at time \( \tau \). The measured value becomes

\[
x_n = g(n)s_n
\]

where the suppression factor near biofouling onset, \( g(n) \), is

\[
g(n) = \begin{cases} 1 \\ \left(1 - m(n - \tau)\right) \end{cases} \quad n < \tau \\
\left(1 - m(n - \tau)\right) \quad n \geq \tau
\]

and \( m \) is the biofouling rate (1/sec). The probability density of measurement \( x_n \) is thus

\[
p(x_n) = \frac{1}{\sqrt{2\pi g(n)\sigma_s}} \exp\left(-\frac{(x_n - g(n)\mu_s)^2}{2g(n)\sigma_s^2}\right)
\]
Both the measurement mean, \( g(n) \mu_n \), and variance, \( g^2(n)\sigma_n^2 \), decrease as biofouling progresses. 

[22] Using these models for clean and biofouled salinity signals, we now write the SLR for md salinity. The values for the biofouling rate \( m \) and onset time \( \tau \) are not known in advance, so we replace them with their maximum likelihood estimates. The SLR is

\[
 h = \max_{\tau,m} \sum_{n=\tau}^{N} \ln \left( 1 - m(n-\tau) \right) + \frac{(x_n - \mu_n)^2}{2\sigma_n^2} \\
- \frac{(x_n - (1-m(n-\tau))\mu_n)^2}{2(1-m(n-\tau))^2}\gamma
\]  

When a sequence of measurements fits the biofouled model better than the clean model, the second term in (8) is large and the third term is small, so \( h \) is positive. Consequently, when \( h \) is above a chosen threshold, the sensor will be classified as biofouled. The threshold is chosen to satisfy operational requirements. For this work, we choose thresholds so that the classifiers have low false alarm rates.

[23] Incorporating temperature information into SLR tests should improve classification accuracy. The appropriate SLR is the log probability of md salinity conditioned on temperature given the biofouling model divided by the probability given the clean model. We start by modeling the salinity, \( s \), and temperature-based mixing coefficient, \( \alpha \), as jointly Gaussian,

\[
p(s, \alpha) = N(\mu, \Sigma)\text{where }\mu = \begin{bmatrix} \mu_s \\ \mu_\alpha \end{bmatrix} \text{ and } \Sigma = \begin{bmatrix} \sigma_s^2 & \sigma_s\sigma_\alpha \\ \sigma_s\sigma_\alpha & \sigma_\alpha^2 \end{bmatrix}. \tag{9}\]

The probability of md salinity conditioned on temperature when the sensor is clean is Gaussian with \( N(\eta, \gamma) \), where the mean is the expected value of md salinity given temperature,

\[
E[s | \alpha] \equiv \eta = \mu_s + (\sigma_{s\alpha}/\sigma_s^2)(\alpha - \mu_\alpha) \tag{10}
\]

and the variance

\[
\text{var}[s | \alpha] \equiv \gamma = \sigma_s^2 - \sigma_{s\alpha}^2/\sigma_s^2 \tag{11}
\]

Since the temperature sensor is not susceptible to biofouling, we do not have to consider the case of both sensors degrading at the same time. When biofouling occurs, the salinity measurement is suppressed relative to the true value. Using the suppression factor \( g(n) \) (6), the probability of the salinity measurement, \( x \), conditioned on temperature is \( p(x_n|\alpha_n) = N(g(n)\eta_n, g^2(n)\gamma_n) \). The SLR for salinity conditioned on temperature is then given by

\[
 h = \max_{\tau,m} \sum_{n=\tau}^{N} \ln \left( 1 - m(n-\tau) \right) + \frac{(x_n - \eta_n)^2}{2\gamma} \\
- \frac{(x_n - (1-m(n-\tau))\eta_n)^2}{2(1-m(n-\tau))^2}\gamma
\]  

When \( h \) is above our chosen threshold, the sensor is classified as biofouled.

4.3. Model Fitting

[24] The SLR classifier parameters, \( \mu \) and \( \Sigma \) are determined from clean example data; no biofouled examples are necessary. We find maximum likelihood estimates for these parameters from archival data, \( (s_n, \alpha_n), n = 1 \ldots N \). The mean values are given by

\[
\mu = \frac{1}{N} \sum_{n=1}^{N} \begin{bmatrix} s_n \\ \alpha_n \end{bmatrix}
\]

The salinity and temperature covariance matrix, \( \Sigma \), is given by

\[
\Sigma = \frac{1}{N} \sum_{n=1}^{N} \begin{bmatrix} s_n - \mu_s \\ \alpha_n - \mu_\alpha \end{bmatrix} \begin{bmatrix} s_n - \mu_s & \alpha_n - \mu_\alpha \end{bmatrix}^T
\]

All other classifier parameter values, such as \( \mu_\alpha \) or \( \text{E}[s|\alpha] \), can be extracted or calculated from the mean vectors and covariance matrix as given by equations (9), (10), and (11).

[25] To use SLR tests for biofouling detection, we determine the biofouled model parameters for the current sensor data and calculate \( h \), (8) or (12), for the current time. At each time step, \( n \), the onset time \( \tau \) and biofouling rate \( m \) are fit by maximum likelihood methods to the past and current measurements. The SLR \( h \) is then calculated using these estimates. If \( h \) is above our threshold, the current measurement is classified as biofouled and the onset time is reported as \( \tau \).

[26] To determine the onset time estimate, \( \tau \), we search for the SLR window length that maximizes the likelihood of the data assuming it is biofouled. This search begins at the time the sensor was installed and ends at two days before the current time, so that

\[
\tau = \arg \max_k \sum_{n=k+1}^{N} \ln p(x_n | f; m_{N-k})
\]  

where \( N \) is the current time and our notation \( m_{N-k} \) stresses that the biofouling rate is a function of the window length \( N - k \). For each possible value for \( \tau \), that is \( k = 3 \ldots N \), we first determine the maximum likelihood estimate for \( m_{N-k} \) (described below) and then calculate the corresponding SLR \( h_{N-k} \). The estimated onset time, \( \tau \), is the time \( k \) that gives the largest likelihood value.

[27] For the salinity alone SLR, we find the maximum likelihood estimate of biofouling rate \( m \), by setting the first derivative of (8) with respect to \( m \) equal to zero. This operation yields the relation

\[
m \sum_{k=\tau+1}^{N} \frac{(k-\tau)^2}{\omega_k^2 - \mu_s^2} = \sum_{k=\tau+1}^{N} \frac{k - \tau}{\omega_k} \left( \frac{(x_k - \mu_s)\omega_s}{\omega_k\sigma_s^2} + \frac{(x_k - \omega_s\mu_s)^2}{\omega_k^2} \right)
\]

where \( \omega_k = 1 - m(k - \tau) \) and \( N \) is the current time. Note that \( m \) appears both at the beginning of (16) and in the
definition of $\omega$, so we do not have a closed form solution for $m$. The $\omega$ values act as weights that increase the importance of most recent measurements. This weighting accounts for the expected decrease in measurement variance as biofouling progresses. To estimate $m$ we take an iterative approach. First, initialize $m$ to its minimum mean squared error (mse) value given by

$$m^{(0)} = \frac{\sum_{k=t+1}^{N}(k-\tau)(x_k-\mu_k)w_k}{\sum_{k=t+1}^{N}(k-\tau)^2 w_k^2}$$  \hspace{1cm} (17)$$

Second, repeatedly solve (16) for $m^{(i)}$ with $w$ calculated using the previous value $m^{(i-1)}$. The estimated rate value stops changing when the likelihood reaches a maximum. On a practical note, we found that using the simpler mse calculation (17) to find the biofouling rate $m$, instead of the iterative calculation of (16), did not measurably degrade classifier performance.

[28] For the salinity conditioned on temperature SLR, $m$ is found by maximizing (12). The results are similar to (16) and (17) with $\mu_k$ replaced by $\eta(10)$ and $\sigma^2_s$ replaced by $\gamma (11)$. The classification procedure is the same as that for salinity alone SLR tests.

[29] SLR tests meet our classifier requirements. By parameterizing the biofouling model, we are able to develop the SLR test classifiers exclusively on clean example data. The biofouled model parameters are fit to the data under test. SLR tests classify a sequence of measurements, so that long salinity downtrends produce larger $h$ values than do short downtrends. The strong response to sustained salinity decreases should increase our confidence in biofouling decisions. Finally, SLR tests provide an estimate of onset time by finding the time when the measurements switch from matching the clean model to matching the biofouled model.

5. SLR Test Evaluation

[30] We evaluated classification accuracy, time to detection, and onset time accuracy of our SLR classifiers on CORIE test data. Classification accuracy is reported using Receiver Operating Characteristic (ROC) curves. An ROC plots the percentage of false alarms against percentage of correct detections for a range of threshold values. Time to detection is the time difference between biofouling onset and the earliest time our classifiers correctly identify that the sensor is biofouled. We compare time to detection of our SLR classifiers to the time it takes a human expert to visually identify that the sensor is biofouled. For onset time evaluation, we simulated biofouled signals by applying a linear degradation function to clean salinity measurements. We compare the estimated onset time provided by our SLR classifiers with the known onset time.

5.1. Classifier Accuracy

[31] To evaluate classifier accuracy, we use ROC curves. An ROC provides the information to assess detector performance for any operating condition. It plots percentage of false alarms (identify clean signal as biofouled) against percentage of correct detections (identify biofouled signal as biofouled) for a range of detector threshold values. An ideal classifier has 100% detection with no false alarms. Due to the overlap between clean and early biofouled measurements, we can not achieve ideal classification. We are interested in achieving a high rate of detection at a low false alarm rate (<5%), since replacing instruments is expensive in terms of time and resources.
[32] To accurately characterize classifier performance we must use our small data set effectively. There are too few examples to divide the data into fixed development (training) and test sets, so we use a hold-out method instead. For hold-out, we develop a series of classifiers. Each classifier is trained using all but one of the example time series segments and is tested on the held-out segment. Each time series segment is held-out in turn. The results from these classifiers are combined to form a single ROC, which gives a conservative estimate of classifier performance [Fukunaga, 1990].

[33] We compared the classification accuracy of our salinity alone SLR classifier, $\text{SLR}(s)$, to that of salinity conditioned on temperature SLR classifier, $\text{SLR}(s|\alpha)$. The ROC curves for Sand Island, Tansy Point, and Astoria-Megler are shown in Figure 6. The false alarm rate is plotted on a logarithmic scale to enhance evaluation at low false alarm rates.

[34] At Sand Island, the $\text{SLR}(s)$ classifier identified 65% of the biofouled days correctly at a false alarm rate of 1%. When temperature is included, the biofouling detection increases to nearly 90% at the same false alarm rate. At Tansy Point, the $\text{SLR}(s)$ classifier correctly identifies 70% of the biofouled days and the $\text{SLR}(s|\alpha)$ classifier 81% of the biofouled days with 1% false alarms. In addition, for the Sand Island and Tansy point sensors, the archive contains enough biofouling examples that we were able to train discriminatory classifiers based on Fisher Linear Discriminant Analysis (LDA) [Bishop, 1995]. These Fisher LDA classifiers correctly identified only 40% of the biofouled measurements from Sand Island and 62% from Tansy Point.

[35] Although the Astoria-Megler station is subject to spring-neap tidal variations, the SLR classifiers still performed well. The salinity alone classifier correctly identifies 69% of the biofouled days with a 1% false alarm rate. Biofouling detection with $\text{SLR}(s|\alpha)$ classifier increase to 86% at the same false alarm rate.

[36] In summary, SLR classifiers for salinity alone have good accuracy at low (≤5%) false alarm rates for all three sensors. Incorporating temperature to recognize normal salinity decreases substantially improves correct detection. In addition, for those sites with enough biofouled archival data to train discriminatory classifiers, we found that our SLR classifiers had better accuracy at low false alarm rates. The SLR classifiers achieve this accuracy without requiring biofouled training examples.

5.2. Detection Delay

[37] Another way to evaluate our classifiers is to examine the time to detection. To minimize data loss and the real-time use of corrupted data, we desire short times to detection. Since the exact time of biofouling onset is uncertain, we compare detection times relative to the onset times estimated visually by a human expert. We selected classifier thresholds to produce less than 1% false alarms on archival clean data. Detection time is the earliest time a discriminant exceeds and stays beyond the corresponding threshold. Included in our evaluation are a field scientist’s estimates of when he would have scheduled a sensor to be cleaned, if he had monitored the salinity signal daily.

[38] Table 1 contains time of detection rounded to the nearest day for each time series segment. Since we have so few examples, we hesitate to make precise comparisons of detection time, but we do note a few general trends. SLR classifiers for salinity conditioned on temperature have detection times comparable to or a few days faster than the human expert. SLR classifiers for salinity alone typically pass their thresholds several days after the field scientist estimates that he would identify biofouling.

[39] To see how well our classifiers worked in practice, we implemented versions that operated on real-time salinity and temperature measurements. The online biofouling indicators plot the $\text{SLR}(s|\alpha)$ discriminant values for the past 40 days. The 1% and 10% false alarm thresholds were overlaid on each plot. The field staff continued their current practice of monitoring the raw times series, while we monitored the online indicators. For all four instances of sensor degradation (three biofouling incidents and one instrument failure that mimicked biofouling) that occurred in the summer 2001 test period, our classifiers correctly indicated a sensor problem before the field staff was aware of it. In addition, the real-time classifiers produced no false alarms during the test period.

[40] Table 7 shows the online biofouling monitor during incidents at the Red26 CT1448 sensor and the Tansy Point CT1462 sensor. Since we had another sensor mounted at the Red26 site that did not biofoul (see Figure 2), we were able to accurately estimate the biofouling onset time as September 28th. The discriminant for our $\text{SLR}(s|\alpha)$ classifier passed the 1% false alarm threshold five days after onset and roughly three days before the field staff decided the instrument needed cleaning. This reduction in time to detection corresponds to reduced data loss of over 30%. In addition, the onset time estimate of September 29th was within a day of the true onset time.

[41] The Tansy Point CT1462 sensor began to biofoul a few days after the Red26 CT1448 sensor. Our SLR classifier indicated that the Tansy Point sensor was biofouling on October 9th. Since neighboring sensor Red26 was being replaced on October 11th, the field staff decided to retrieve the Tansy Point sensor as well. On removal, this sensor was found to be in the early stages of biofouling. In this case,
indications from our classifier permitted the sensor to be
replaced before the field staff would normally have recog-
nized the biofouling and scheduled the sensor for retrieval.
Experience with our online biofouling indicators demon-
strates that these automatic methods reduce the time from
biofouling onset to detection and sensor replacement.

5.3. Onset Time Estimates

[42] One advantage of sequential likelihood ratio tests is
their ability to produce a maximum likelihood estimate of
biofouling onset time. This estimate has the potential to
provide a valuable aid to the staff when making decisions
about data quality. We would like to evaluate the accuracy of
this estimate, but true onset times for our example data are
not known. Instead of using actual biofouled examples, we
generated simulated biofouled time series with degradation
starting at a known time. The simulated time series consist of
clean example data, \( x \), where after the chosen onset time, \( \tau \)
the signal is linearly degraded until some minimum value is
reached. The simulated signal \( y \) at time step \( n \) is thus

\[
y_n = \begin{cases} 
x_n & n \leq \tau \\
(1 - m(n - \tau))x_n & n > \tau \text{ and } m(n - \tau) < 0.5 \\
0.5x_n & \text{otherwise} 
\end{cases} \tag{18}
\]

where \( m \) is the biofouling rate. We chose \( m = 0.016/\text{sec} \),
since rates measured from summer biofouling incidents
ranged from 0.012 to 0.025. We classify the simulated
biofouled data, \( y \), and extract the onset time estimated when
the discriminants first exceed the 1% false alarm thresholds.

[43] Table 2 contains onset time estimates from the SLR
classifiers for several example time series with simulated

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|}
\hline
Site & Segment Year & Onset Day & Onset Err & Onset Day & Onset Err \\
\hline
Sand Island & 1999 & 6/07 & 6/07 & 0 & 6/06 & 1 \\
Tansy Point & 2001 & 6/21 & 7/04 & +3 & 7/04 & 2 \\
Tansy Point & 2001 & 7/02 & 7/15 & +2 & 7/13 & 0 \\
Tansy Point & 2001 & 7/13 & 8/20 & +6 & 8/15 & 1 \\
\hline
\end{tabular}
\caption{Estimated Biofouling Onset Times for Simulated
Biofouling Applied to Sand Island and Tansy Point Data\textsuperscript{a}}
\textsuperscript{a}Times are given as month/day. Onset day is \( \tau \) in (18). Err is difference
between estimated and true onset times. SLR(\( x \)) is the SLR classifier for
salinity alone, and SLR(\( x|a \)) is the SLR classifier for salinity conditioned on
temperature.
\end{table}

Figure 7. Biofouling indicators (a) Red26 and (b) Tansy Point. Top plots show maximum diurnal
salinity. Bottom plots show the SLR(\( x|a \)) discriminant for 40 days of salinity and temperature
measurements. Dotted lines indicate 1% and 10% false alarm rate. The crosses indicates the estimated
biofouling onset time.
biofouling. In general, the onset estimates are within a day or two of true onset. There are a couple of exceptions worth noting. The first is illustrated by the Tansy Point example with onset day 8/14. In this case, the estimate from the SLR(s) classifier is several days after onset. There is a natural increase in salinity at the point where biofouling is applied, so salinity does not decrease until a few days after onset. The SLR(s|a) classifier uses temperature to recognize that salinity should have been increasing and gives a better estimate of onset time.

The only problem found with the onset time estimate is illustrated by the simulated Sand Island example with onset day 6/04. In this case, the time to detection was (correctly) several days after onset, but the onset estimate from both SLR classifiers are early. The md salinity measurements are below the expected value (either $E[s]$ and $E[s|a]$) for over a week before biofouling onset. Hence, the SLR classifiers fit a decreasing trend to both this low md salinity data and the biofouled data. We find that when biofouling occurs during or immediately following a period of low md salinity, the onset estimate is often too early.

6. Discussion

The CORIE observation network includes measurements from CT sensors deployed throughout the Columbia river estuary. These sensors are subject to biofouling, that is the gradual degradation of sensor response due to the accumulation of biological matter on the sensor. To ensure data integrity, we should detect this degradation within a few diurnal cycles of biofouling onset. In this paper, we described our successful initial efforts to develop automatic classifiers for these sensors. In this final section, we discuss limitations of these classifiers and summarize our work.

6.1. Limitations to Biofouling Detection

For our biofouling detectors, we incorporate temperature measurements to recognize normal decreases in md salinity. Exploiting the correlation between salinity and temperature resulted in improved biofouling classification accuracy and reduced times to detection. However, temperature is a useful measure only when the difference in river and ocean temperatures are significantly different. The SLR(s|a) classifiers are not effective during times of year or in estuary systems with small river and ocean temperature differences. In the Columbia estuary, these temperatures are close together for several weeks in both the spring and fall. During these periods, we currently rely on the SLR(s) classifier for biofouling detection. However, the salinity alone classifier will perform poorly when the md salinity value is significantly nonstationary due to either spring-neap fluctuations or changes in river (fresh water) flow.

In developing the SLR(s) classifiers, we assumed that the md salinity measurements varied around some stationary mean value. In the Columbia estuary, there are occasionally periods of depressed md salinity that appear to be related to increases in river flow. The measurements that occur during these periods are incorrectly identified as biofouled, making them the primary source of false alarms. In addition, biofouling onset time estimates are too early when md salinity is lower than expected. Consequently, the biofouling detectors presented here can not be applied directly in estuary systems where increases in fresh water flow and biofouling are concurrent. However, biofouling detection with SLR tests can still be effective. River flow or some measure of fresh water runoff can be used instead of temperature to recognize decreases in salinity due to increases in fresh water flow.

The SLR(s) classifiers performed adequately for the sensors evaluated in this paper, including those with mild spring-neap variability. However, the CORIE inner estuary stations (e.g., coaww or moth in Figure 1) display strong spring-neap variability to the extent that we measure negligible md salinity during weak tides. SLR(s) detectors at these high-variability stations generate many false alarms. In future work, we plan to investigate the use of depth and river flow information to determine expected values for md salinity at these stations. If successful, SLR classifiers that incorporate these measurements should provide effective biofouling detection for sensors in estuaries with strong spring-neap variability.

6.2. Summary

Prior to this work, no automatic biofouling detection existed for the CORIE salinity sensors. The field staff identify biofouling by periodic visual examination of the time series. Our work involved development of automatic biofouling detectors using sequential likelihood ratio tests for salinity and salinity conditioned on temperature. These SLR classifiers have several advantages: they accrue information over time to improve classification accuracy, they provide an estimate of biofouling onset time, and they do not require extensive amounts of biofouled data examples to develop.

Our biofouling detectors performed well on both archival evaluation data and in online experiments. On the archival data, the SLR classifier for salinity alone correctly identified 65% to 80% of the biofouled measurements correctly at a classifier threshold that produced 1% false alarms. Incorporating temperature information improved classification accuracy by around 10%. The SLR classifier for salinity conditioned on temperature correctly identified 80% to 90% of biofouled measurements. This classification error rate corresponds to a delay between onset and detection that is comparable to that of human experts. Classifiers deployed online during summer 2001 detected all four episodes of sensor failure before the field staff noticed the signal degradation. These real-time detectors generated no false alarms during the test period.

Two of our test cases indicates that our SLR classifiers may be effective in solving the difficult problem of detecting slow growth biofouling. Slow growth biofouling, when the degradation occurs gradually over several months, is difficult to detect visually. Most of the test cases presented in this paper were incidents of fast hard-growth biofouling. However, the 1999 segment from Tansy Point and 1998 segment from Astoria-Megler (see Table 1) are cases of biofouling with slow fitful degradation. Our expert identified biofouling on the Tansy Point segment around seventy-five days after onset and on the Astoria-Megler segment around thirty days after onset. However, in both cases the SLR(s|a) classifiers detected biofouling only nine days after onset. These two test cases indicate that our automatic detectors have the potential to recognize slow-
growth biofouling quickly. Motivated by these results, we are currently extending the SLR(s|α) classifiers to operate during the winter months when biofouling growth is especially slow and difficult to detect visually.

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