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TECHNICAL DIAGNOSTICS OF MARINE EQUIPMENT WITH PSEUDO-DISCRETE FEATURES

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Abstract. We present a system for technical diagnostics (TD) that can recognize the actual state of marine equipment. A Bayesian classifier is trained to identify the different classes of a piece of equipment, monitored through multiple pseudo-discrete features. Data learning samples can be acquired with direct experiments for each class. The system is capable of merging subjective expert knowledge and data learning samples using pseudo-Bayesian estimates when the parameters of the conditional likelihood for the classes are identified. In the training process, ε correction is applied to solve numerical problems arising from zero probabilities. The pseudo-discrete features have hybrid nature and unite probabilistic and fuzzy approaches. They combine the ease of extracting subjective expert knowledge typical for discrete features with the high precision of using the measured data during recognition typical for continuous features. The domain of each pseudo-discrete feature is divided into several main categories of non-overlapping intervals, which are described as words by the expert. If a measured feature falls between two consecutive categories it is treated as a linear combination of those categories. The resubstitution performance of the classifier is assessed using an error matrix. A numerical example of a marine diesel generator demonstrates the proposed algorithm in a classification problem with nine different state classes of the generator, monitored through 23 pseudo-discrete features. Data learning samples are acquired with direct experiments for each class. The created TD system has potential applications in other complex engineering systems and may support improvements in marine engineering education and training.

Keywords: Fuzzy-probabilistic merging, pseudo-Bayesian parameter estimation, learning information, pattern recognition

1. Introduction

The technical diagnostics (TD) process has been a topic rising in popularity, as industry continues to seek ways to lower expenditures on maintenance and minimize system downtime losses. With the aid of reliability engineering, the process of recognizing the working status of any machine or complex system into classes (Koc et al., 2012) has been simplified immensely. However, with a complex system or complex piece of machinery, the diagnostic process remains tedious for maintenance personnel. More and more unexperienced personnel, or staff unfamiliar with the operations of such systems get in charge of maintenance/monitoring. Without good knowledge of the proper workings of such systems, diagnosis of potential faults becomes problematic, since they often face large amount of monitored data without knowing the meaning of it.

In this paper, we introduce a TD system using a multi-class classifier, based on pseudo-discrete features (Nikolova et al., 2019). We shall demonstrate the application of the system to recognize the actual state of a hypothetical marine diesel generator in a numerical example. We shall train a Bayesian classifier to identify nine different state classes of the equipment, monitored through 23 pseudo-discrete features. For the learning process, we shall combine subjective expert knowledge and data learning samples using pseudo-Bayesian estimates (Skaggs, Stevenson, 1989) when the parameters of the conditional likelihood for the classes are identified. We shall apply epsilon correction in the training process to solve numerical problems arising from zero probabilities.

In what follows, section 2 presents the structure of the technical diagnostics system, the structure of the information we shall utilize to train the classifier and the epsilon corrections we shall apply. The application of the Bayesian classifier to a numerical example for the hypothetical MTU 8V396 marine diesel generator is presented in section 3. Section 4 concludes the paper.

2. State identification

2.1. Bayesian Classification

Let us analyze a complex system (or a system component) with c working states, aka classes $\omega_k\ (k=1,2,...,c)$. To monitor the system's working state (or class), a feature column vector $\vec{X}$ is introduced as a d-dimensional measurement of properties containing diagnostic information about the states (e.g. temperature, pressure, flowrate, displacement, etc.), where each measured property is a pseudo-discrete feature, represented with the real number x_i, $i=1,2,...,d$

$$\vec{X}=\left(x_1,x_2,\ldots,x_d\right)^T$$

We assume that the d-pseudo-discrete features are independent. If the measurements of the system in a given moment of time are organized in $\vec{X}$, then for each class $\omega_k\ \left(k=1,2,...,c\right)$ we seek to identify the posterior probability, $P\left(\omega_k\mid\vec{X}\right)$, of the system to be in a that class. The necessity to use the Bayesian theorem for updating anyone's degree of belief based on new information (which is contained in the values of the specific measurement $\vec{X}$) is proven using rational behavioristic assumptions (French, 1993). So, the posterior probabilities will be identified using the Bayesian theorem (Ebeling, 2010):

$$P\left(\omega_k \mid \vec{X}\right) = \frac{P\left(\omega_k\right) P\left(\vec{X} \mid \omega_k\right)}{P\left(\vec{X}\right)} \qquad \textbf{(2)}$$

The initial probabilities of each class $P\left(\omega_k\right), \left(k = 1, 2, ..., c\right)$ are known as priors and can be identified by historic reliability data. The priors are positive real numbers that sum to one. The quantiles $P\left(\vec{X} \mid \omega_k\right)$ are the conditional likelihoods of observing the specific measured feature vector $\vec{X}$ given that the state of the system is ω_k. For any feature vector and for any state the conditional likelihoods should be non-negative real values with at least one positive value:

$$\sum_{k=1}^{c} P^2\left(\vec{X} \mid \omega_k\right) > 0 \qquad \textbf{(3)}$$

The quantity $P\left(\vec{X}\right)$ is the unconditional likelihood of observing the specific measured $\vec{X}$ calculated as the total probability formula (Selvanathan et al., 2020):

$$P\left(\vec{X}\right) = \sum_{k=1}^{c} P\left(\omega_k\right) P\left(\vec{X} \mid \omega_k\right) \qquad \textbf{(4)}$$

The unconditional likelihood will always be positive, ensuring that the posterior probabilities will be non-negative and will sum to one for any observed $\vec{X}$.

Due to the independence of the pseudo-discrete features, the conditional likelihoods for $k = 1, 2, 3, ..., c$ can be expressed as:

$$P\left(\vec{X} \mid \omega_k\right) = \prod_{i=1}^{d} P\left(x_i \mid \omega_k\right) \qquad \textbf{(5)}$$

We will call a Bayesian classifier every mathematical tool which accepts as input the measured feature vector $\vec{X}$ and produces as output the posterior probabilities, $P\left(\omega_k \mid \vec{X}\right)$, for $k = 1, 2, \ldots, c$. Sometimes other classification methods are used for maintenance of technical systems (e.g. maximum profit, minimum risk, maximum conditional likelihood, etc. (see (Duda et al., 2001; Fukunaga, 1990)). The Bayesian classifier has several advantages. First, it extracts all the diagnostic information in $\vec{X}$ and combines it with historic reliability data about the states of the system. Second, its result can be fed into expected utility maximisation systems for selecting the best maintenance actions (Nikolova et al., 2019).

2.2. Pseudo-discrete Features

We will discuss the advantages of the pseudo-discrete features in comparison with the continuous and with the discrete features. Take an air compressor as an example. For simplicity, we can define three possible classes for the compressor: normal operation, air leak, and overheating (ω_1, ω_2 and ω_3). To monitor these classes, we measure four pseudo-discrete features: air pressure, air flowrate, oil pressure and oil temperature, i.e., $\vec{X} = \left(x_1, x_2, x_3, x_4\right)^T$.

Measurements from each pseudo-discrete feature are recorded for analysis. An operator may have to make a judgement based on the information presented in **Table 1**.

Table 1. Numerical Data Presentation

Air Pressure x_1	200 kPa
Air Flowrate x_2	1.5 kg/s
Oil Pressure x_3	50 kPa
Oil Temperature x_4	40 degrees Celsius

By looking at the numbers presented in **Table 1**, it is exceedingly difficult for anyone to decide upon the class that the compressor is working in. However, the decision making would be much easier if the person is presented with system information as in **Table 2**. It presents a much clearer picture of the system's working status. Even a person not familiar with the compressor's normal working condition could tell that the compressor is likely overheating.

Table 2. Pseudo-Discrete Presentation

Air Pressure x_1	Normal
Air Flowrate x_2	Normal
Oil Pressure x_3	High
Oil Temperature x_4	Critical

Therefore, we aim to build a technical diagnostic system, using simple pseudo-discrete features that are easy to understand, thus substantially simplify the process of extracting expert knowledge. At the same time, the measurement vectors will contain continuous information as in **Table 1**, which facilitates the precision of extracting the knowledge in the learning data samples and the recognition of specific measurement vectors. So, the pseudo-discrete features act as discrete ones in the process of expert information extraction, but behave like continuous features when dealing with the specific measurements. Each pseudo-discrete feature x_i is categorized into hi typical pseudo-discretes Tj,i, for j=1,2,…,hi. The latter allows us to characterize any specific measurement of xi in categories such as "too high", "high", "normal", "low" and "too low". Let the jth typical pseudo-discrete of the ith pseudo-discrete feature is described as a fuzzy set with degree of membership $\mu_{j,i}\left(x_i\right)$. As any degree of membership function, the values of $\mu_{j,i}\left(x_i\right)$ are non-negative with maximum value of 1 which is achieved at least once:

$$\mu_{j,i}\left(x_i\right)\in\left[0,1\right],\ \forall x_i\in R \qquad \textbf{(6)}$$

$$\mu_{j,i}\left(x_i\right)=1,\ \exists x_i \in R \qquad \textbf{(7)}$$

We would like the pseudo-discretes to form a fuzzy partition of the real line, so we restrict the degree of membership to have forms that sum to one for any real xi value:

$$\sum_{j=1}^{h_i}\mu_{j,i}\left(x_i\right)=1,\ \forall x_i \in R \qquad \textbf{(8)}$$

In the ideal case, the count hi of the pseudo-discretes, their names Tj,i, and the degree of membership function $\mu_{j,i}\left(x_i\right)$ should be designed by experts in the field of technical diagnostics. All formulae in this paper will utilize the generic form of the fuzzy degree of membership function, which satisfies only conditions (6), (7) and (8). However, the developed software and the examples will utilize trapezoidal fuzzy degree of membership functions, as in Figure 1.

Let Dj,i and Uj,i, for j=1,2,…,c are numbers from the extended real line, which satisfy:

$$\begin{aligned} &D_{j,i}<U_{j,i},\ \text{for } j=1,2,...,h_i \\ &U_{j,i}<D_{j+1,i},\ \text{for } j=1,2,...,h_i \end{aligned} \qquad \textbf{(9)}$$

Then, for j=2,3,…,hi-1, the degrees of membership are:

$$\mu_{j,i}\left(x_i\right)=\begin{cases} 0, & x_i \le U_{j-1,i} \\ \dfrac{x_i-U_{j-1,i}}{D_{j,i}-U_{j-1,i}}, & U_{j-1,i}<x_i<D_{j,i} \\ 1, & D_{j,i}\le x_i \le U_{j,i} \\ \dfrac{D_{j+1,i}-x_i}{D_{j+1,i}-U_{j,i}}, & U_{j,i}<x_i<D_{j+1,i} \\ 0, & D_{j+1,i}\le x_i \end{cases}$$

For j=1, the degree of membership is:

$$\mu_{1,i}\left(x_i\right)=\begin{cases}1, & x_i \le U_{1,i}\\ \dfrac{D_{2,i}-x_i}{D_{2,i}-U_{1,i}}, & U_{1,i}<x_i<D_{2,i}\\ 0, & D_{2,i}\le x_i\end{cases}$$

For j=hi, the degree of membership is:

$$\mu_{h_i,i}\left(x_i\right)=\begin{cases}0, & x_i \le U_{h_i-1,i}\\ \dfrac{D_{h_i,i}-x_i}{D_{h_i,i}-U_{h_i-1,i}}, & U_{h_i-1,i}<x_i<D_{h_i,i}\\ 1, & D_{h_i,i}\le x_i\end{cases}$$

In this setup, the values of $D_{1,i}$ and $U_{h_i,i}$ are irrelevant.

Using the same air compressor example, the pseudo-discrete feature x4 (oil temperature in oC) is divided into h4=4 typical discretes: T1,4=”low”, T2,4=”normal”, T3,4=”high” and T4,4=”critical”, with corresponding temperature ranges assigned as shown in **Table 3**. The corresponding fuzzy degrees of membership are given in **Figure 1.**

Table 3. Division of pseudo-discretes
for pseudo-discrete feature Oil Temperature

Low	Below 30 °C
Normal	40-60 °C
High	70-90 °C
Critical	Above 100 °C

Let $q_{j,i}^{k}$ be the probability that pseudo-discrete feature xi is Tj,i provided that $\vec{X}$ belongs to class ω_k (see (Tenekedjiev et al., 2006) for details). For example, the conditional probability of the air compressor being in third class (overheating), with the fourth pseudo-discrete feature (oil temperature) being in the second pseudo-discrete h_2 (normal), is represented as:

$$P\left(x_4 = T_{2,4} = 'normal' \mid \omega_3\right) = q_{2,4}^3 = 0.2$$

The uncertainty in xi can be described by c conditional probability mass functions PMFi,k (for k=1,2,…,c) as follows:

$$PMF_{i,k} = \left\{\left(T_{1,i}, q_{1,i}^k\right), \left(T_{2,i}, q_{2,i}^k\right), \ldots, \left(T_{h_i,i}, q_{h_i,i}^k\right)\right\} \quad \textbf{(10)}$$

As in every PMF, the probabilities should be non-negative and sum to 1:

$$\sum_{j=1}^{h_i} q_{j,i}^k = 1;\ i = 1, 2, \ldots, d; k = 1, 2, \ldots, c \quad \textbf{(11)}$$

Then, the quantity $P\left(x_i \mid \omega_k\right)$ in (5) can be calculated as weighted average of the pseudo-discrete probabilities $q_{j,i}^k$ with weights - the fuzzy degrees of membership:

$$P\left(x_i \mid \omega_k\right) = \sum_{j=1}^{h_j} \mu_{j,i}\left(x_i\right) q_{j,i}^k \quad \textbf{(12)}$$

2.3.1. Expert knowledge extraction

Assume that for class ω_k we do not have any data and should rely entirely on expert information. The expert knowledge extraction for the pseudo-discrete feature xi is much easier to do in comparison with the case when the feature is continuous. The expert workload is the same as if xi is a discrete feature. For each class ω_k and for each feature xi the export has to assess the values of the PMFi,k that are $\left(q_{1,i}^{k(e)}, q_{2,i}^{k(e)}, \ldots, q_{h_i,i}^{k(e)}\right)$ provided that there are only typical cases. The extracted values should be non-negative and satisfy (12). We can then build an expert knowledge $PMF_{i,k}^e$ for the i^{th} pseudo-discrete feature if it belongs to class ω_k. Using (10) and (13), the $PMF_{i,k}^e$ can be written in short form:

$$PMF_{i,k}^{e} = \left(q_{1,i}^{k(e)}, q_{2,i}^{k(e)}, \ldots, q_{h_i,i}^{k(e)}\right) \quad \textbf{(14)}$$

A confidence factor $L_i^{k(e)}$ is applied to the expert estimate of $PMF_{i,k}^{e}$. The factor is positive with maximal value of one and reflects the expert's confidence when assigning probabilities to each pseudo-discrete within a given class. Applying the confidence factor to (14) gives the expert knowledge data base for class ω_k:

$$E_k = \left\{PMF_{i,k}^{e} - L_i^{k(e)} \mid i = 1,2,\ldots,d\right\} \quad \textbf{(15)}$$

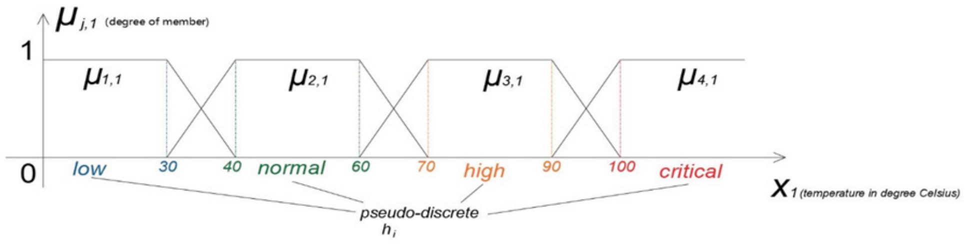

Figure 1. Fuzzy membership Function for Pseudo-discrete feature oil temperature with four pseudo-discretes

2.3.2. Extraction from learning sample

Assume that for class ω_k we only have a learning sample containing nk examples of the feature vector $\vec{X}$:

$$\chi^k = \left\{\left(\vec{X}_l^k, L_l^k\right) \mid l = 1,2,\ldots,n_k\right\} \quad \textbf{(16)}$$

Each measured vector $\vec{X}_l^k$ in χ^k is accompanied by a representation factor L_l^k. The factor is positive with maximal value of one and represents how well $\vec{X}_l^k$ truly represents the class ω_k i.e. the corresponding faults or class of a machine (Hald, 2007). The vector $\vec{X}_l^k$ has the following coordinate notations:

$$\vec{X}_l^k = \left(x_{l,1}^k, x_{l,2}^k, \ldots, x_{l,d}^k\right)^T \quad \textbf{(17)}$$

In the air compressor case, $\vec{X}_{25}^3$ will be:

$$\vec{X}_{25}^3 = \left(x_{25,1}^3, x_{25,2}^3, x_{25,3}^3, x_{25,4}^3\right)^T = \left(101, 1.5, 200, 88\right)^T$$

It represents readings from all four pseudo-discrete feature of the 25th observation, when the compressor is overheating (the air pressure reads 101 kPa, the air flow rate reads 1.5 kg/s, the oil pressure reads 200 kPa, and the oil temperature reads 88 Co).

The parameter $q_{j,i}^{k(x)}$ from (13) can be calculated using the frequentist definition of probabilities (Tenekedjiev et al., 2002):

$$q_{j,i}^{k(x)} = \sum_{l=1}^{n_k} L_l^k \mu_{j,i}\left(x_{l,i}^k\right) / \sum_{l=1}^{n_k} L_l^k \qquad \textbf{(18)}$$

2.3.3. Pseudo-Bayesian merging

Assume that for class ω_k, we have both a learning sample χ^k (16) and an expert knowledge data base Ek (15). When merging the learning sample estimate $q_{j,i}^{k(x)}$ and the expert estimate $q_{j,i}^{k(e)}$ into an estimate $q_{j,i}^{k}$, a pseudo-Bayesian approach can be applied as a weighted mean:

$$q_{j,i}^{k} = \frac{20 L_i^{k(e)} q_{j,i}^{k(e)} + \sum_{l=1}^{n_k} L_l^k q_{j,i}^{k(x)}}{20 L_i^{k(e)} + \sum_{l=1}^{n_k} L_l^k} \qquad \textbf{(19)}$$

The coefficient 20 in (19) reflects the notion that the expert estimates (when $L_i^{k(e)}=1$) should contain the 5% engineering error. The same 5% accuracy can be obtained from 20 observations with $L_l^k=1$.

2.4. Numerical problems

There is a potential numerical problem with the conditional likelihood term $P\left(\vec{X} \mid \omega_k\right)$ in (2). Due to (5), this term is often a small value, and when it is smaller than the machine epsilon ε, it is treated as 0 in any machine language. To solve the stated numerical problem, $P\left(\omega_k \mid \vec{X}\right)$ is split into two terms by taking its logarithm:

$$\ln P\left(\omega_k \mid \vec{X}\right) = A_k\left(\vec{X}\right) + B\left(\vec{X}\right) \qquad \textbf{(20)}$$

The $B\left(\vec{X}\right)$ part does not depend on the class k, whereas the part $A_k\left(\vec{X}\right)$ is different for each class. Using (2), (5) and (12) we obtain the following:

$$A_k\left(\vec{X}\right)=\sum_{i=1}^{d}\ln\left[P\left(x_i\mid\omega_k\right)\right]+\ln\left[P\left(\omega_k\right)\right]$$
$$=\sum_{i=1}^{d}\ln\sum_{j=1}^{h_j}\mu_{j,i}\left(x_i\right)q_{j,i}^{k}+\ln\left[P\left(\omega_k\right)\right] \quad \textbf{(21)}$$

$A_k\left(\vec{X}\right)$ is called the discriminant function for class k. That name originates from the fact that we can easily identify the class with the greatest posterior probability as the class with the greatest discriminant function (i.e., we can classify the observation $\vec{x}$ using the maximum posterior probability method based only on the discriminant functions):

$$x\in\omega_k \text{ if } A_k\left(\vec{X}\right)\geq A_i\left(\vec{X}\right),\ \forall i \quad \textbf{(22)}$$

Discriminant functions allow to avoid this numerical problem. Although we will never calculate $B\left(\vec{X}\right)$, it is trivial to derive an expression for the posterior probabilities depending only on the discriminant functions:

$$P\left(\omega_k\mid\vec{X}\right)=1/\sum_{j=1}^{c}e^{A_j\left(\vec{X}\right)-A_k\left(\vec{X}\right)} \quad \textbf{(23)}$$

However, using discriminant functions requires no conditional probability to be zero $\left(q_{j,i}^{k}=0\right)$. In this case, the 0 probability is substituted with the machine epsilon ε, while the probabilities from other pseudo-discretes are multiplied by $1-\varepsilon$, so the sum of probabilities from the pseudo-discretes in the same observation is 1 according to (11).

Using the compressor example again, in an observation from the 3rd class "Overheating" (k=3), the 4th pseudo-discrete feature "Oil Temperature" (i=4) has h4=4 pseudo-discretes (low, normal, high, critical). Imagine that $\left(q_{4,4}^{3}=0\right)$. In this case, epsilon correction is performed as shown in **Table 4.**

Table 4. Epsilon Correction for $q_{j,4}^{4}$

Pseudo-Disrete	**Original Observation**	**Epsilon-Corrected Observation**
$q_{1,4}^{4}$	0.2	$0.2(1-\varepsilon)$

$q_{2,4}^{4}$	0.3	$0.3(1-\varepsilon)$
$q_{3,4}^{4}$	0.5	$0.5(1-\varepsilon)$
$q_{4,4}^{4}$	0	ε
Sum	1	1

More practical results may be obtained if we substitute ε with the smallest non-negative $q_{j,i}^{k}$ divided by 1000.

3. Application on Marine Diesel Generator

With the established theoretical and mathematical background, we apply the Bayesian classifier within a numerical example of a hypothetical MTU 8V396 marine diesel generator. The data for our numerical example is obtained from an expert. A total of 9 classes are established, monitored through 23 pseudo-discrete features, i.e., c=9, and d=23. The classes and features are listed in **Table 5** and **Table 6.**

Table 5. List of Classes for the Marine Diesel Generator Example

ω_1	Metal Fatigue
ω_2	Lost of DC Voltage
ω_3	Insufficient Output Frequency
ω_4	Single Phase Voltage Drop
ω_5	Misalignment
ω_6	Faulty Knock in Bore
ω_7	Incorrect Air/Fuel Ratio
ω_8	Cooler Overheating
ω_9	Normal Operation

After consulting with an expert, the pseudo-discrete features are classified into 3 to 5 different pseudo-discretes, with ranges $\left[D_j, U_j\right]$ given to each pseudo-discrete, and expert knowledge $q_{j,i}^{k(e)}$ given to every pseudo-discrete of every pseudo-discrete feature under every class.

A learning sample, containing 10 observations in each class are given to the Bayesian classifier for learning and recognition. The confidence factor applied to the expert knowledge is set at 100% for this analysis.

To demonstrate the parameter estimation methods and to test the performance of the classifier the expert also provided 10 pseudo observations to each class. Some of the observations are purposely put out of $\left[D_j, U_j\right]$ for some pseudo-discrete features to see if the classifier would recognize them as being in a different class.

Table 6. List of Pseudo-Discrete Features for the Marine Diesel Generator Example

x_1	DC Voltage (V)
x_2	Oil Pressure (psi)
x_3	Oil Flowrate (L/min)
x_4	Oil Temperature (K)
x_5	Water Temperature (K)
x_6	Water Flowrate (L/min)
x_7	Boost Pressure (bar)
x_8	Boost Temperature 1 (K)
x_9	Boost Temperature 2 (K)
x_{10}	Speed (rpm)
x_{11}	Drive-end tri-axel Accelerometer x (mm/s)
x_{12}	Drive-end tri-axel Accelerometer y (mm/s)
x_{13}	Drive-end tri-axel Accelerometer z (mm/s)
x_{14}	Non-drive-end tri-axel Accelerometer x (mm/s)
x_{15}	Non-drive-end tri-axel Accelerometer y (mm/s)
x_{16}	Non-drive-end tri-axel Accelerometer z (mm/s)
x_{17}	Output Frequency (Hz)
x_{18}	Bank A Knock Censor (mm/s)
x_{19}	Bank B Knock Censor (mm/s)
x_{20}	U Single-Phase AC Voltage (V)
x_{21}	V Single-Phase AC Voltage (V)
x_{22}	W Single-Phase AC Voltage (V)
x_{23}	Fule Flowrate (L/hr)

After recognition, the Bayesian classifier produces a confusion matrix that can be summarized as:

ω1: 8 observations recognized correctly;
2 observations recognized in class9;
ω2: 8 observations recognized correctly;
1 observation recognized in class 8;
1 observation recognized in class 9;
ω3: 5 observations recognized correctly;
3 observations recognized in class 4;
2 observations recognized in class 9;
ω4: All observations recognized correctly;
ω5: 9 observations recognized correctly;
1 observation recognized in class 9;
ω6: 8 observations recognized correctly;
1 observation recognized in class 5;
1 observation recognized in class 9;
ω7: 9 observations recognized correctly;
1 observation recognized in class 9;
ω8: All observations recognized correctly;
ω9: 9 observations recognized correctly;
1 observation recognized in class 8.

4.Conclusion

The process of applying pseudo-discrete features to complex systems could drastically simplify the technical diagnosis process. Our Bayesian classifier was able to recognize the state of the hypothetical generator with few errors on the majority of the 90 pseudo observations provided by the expert. Given sufficient and accurate/confident expert knowledge, the classifier is able to accurately recognize the pattern within the measured pseudo-discrete features.

The use of pseudo-discrete features improves the quality of education in marine engineering, where students need pattern classification in technical diagnostics of marine equipment. These features are easy to use and comprehend. The pattern classification process is more transparent in that way because students can track the diagnostics decisions to their knowledge on how the marine equipment operates.

Future tests of the system should include actual recorded data from running the generator under different conditions, and some expert datasets should be made unavailable. The classifier would have to perform under two additional scenarios: only learning sample data available with no expert knowledge; only expert knowledge available with no learning sample. The created classification approach with pseudo-discrete features has potential application in other complex engineering systems and in medical diagnostics.

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