

# Hidden Markov Model-Based Detection and Classification of Foreign Objects in Heat-Exchanger Tubes

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## ABSTRACT

In recent years, there has been significant interest in prognosis and health management of heat exchanger tubes in steam generators (SG) using eddy current (EC) non-destructive evaluation (NDE) techniques. One of the recent challenges encountered in SG tube inspection is the presence of foreign objects lodged outside the tubes. Extreme vibrations cause these loose parts to rub against the tube wall and form wears on their outer surfaces which can be dangerous in the high pressure environment. Hence, there is a strong need for reliable automated signal analysis systems for early detection of foreign objects and prevention of harmful radioactive leaks at nuclear facilities. In this paper, a hidden Markov model (HMM) based classifier is proposed which can estimate the material of the foreign object from EC inspection signal. Unknown loose part material interferes with EC analysis results and lead to errors in signal processing parameters which in turn can degrade performance and reliability of automated detection systems. The proposed algorithm implements a continuous HMM classifier by using magnitude and phase based measurements obtained from the foreign object. Results of applying the algorithm on experimental data from SG tube inspection is presented, demonstrating its benefits in increasing the robustness and performance of automated signal analysis systems in detecting loose parts.

## 1. INTRODUCTION

Assessing structural integrity of heat exchanger tubes is a challenging task faced by the Non Destructive Evaluation (NDE) industry. High temperature, pressure, material interactions and fluid flow rates cause various types of degradations on the tube walls. These multiple cracks potentially lead to leakage of harmful radioactive fluids into the environment and hence periodic inspection of steam generator tubes is imperative. With the rise in unscheduled plant shutdowns

in recent years and increase in repair costs, industries have started demanding more accurate and consistent determination of flaws in heat exchanger tubes.

Automated data analysis systems have gained a lot of popularity in steam generator (SG) tube inspection to detect flaws in tubes (Udpa, Ramuhalli, Benson, & Udpa, 2004; Xiang et al., 2000; Grimberg et al., 2011). As newer forms of subtle degradation mechanisms have been identified over the years, more advanced signal processing techniques are implemented in the existing data analysis systems. Often in industry, different inspection conditions cause noise and unwanted signal interference which makes the task of damage characterization more complex. Additional difficulties in NDE data analysis arise due to signals from probe wobble, support structures and variations in geometry of tubes. Along with cracks and wears, a more recent challenge faced by the industries is monitoring the presence of foreign objects outside tube walls. These are parts of the tube or its surrounding structures which break off and lodge outside the tube wall. Due to continuous vibrations, they rub against the wall leading to thinning and cracks on their outer surface. Consequently, early detection of foreign objects is necessary to improve the health of SG tubes and it is important to develop reliable automated signal analysis systems for the same. The method proposed in this paper aims at improving existing techniques for loose part characterization.

Eddy current testing (ECT) has been used for decades as a standard NDE method for periodic maintenance of SG tubes (Grimberg et al., 2011). Presence of a crack or anomaly in conducting materials causes variation in the coil impedance which is captured by change in phase and amplitude of the EC inspection signal. This technique is highly sensitive to detect surface as well as sub-surface cracks or pitting in non-ferromagnetic or partially-ferromagnetic materials such as nickel alloys used in SG tubing. ECT has further proved to be successful in detecting loose parts in SG tubes depending on the size of the loose part and its distance from the outer wall of the tube (Joo & Shina, 2012). Automated data analy-

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sis systems have been developed to process eddy current inspection signals and detect regions-of-interest (ROI) indicating possible loose parts with higher accuracy and consistency. Subsequently, magnitude and phase based features extracted from the ROIs are analysed by a rule-based or other statistical classifiers in order to classify a ROI as a loose part or noise indication (Mayo & Shugars, 1988). However, to the best of author's knowledge, classification at a sub-level, precisely for estimating the material of loose part has not yet been addressed yet. Eddy current signals depend strongly on material properties of the object specifically its conductivity and magnetic permeability and hence loose parts of different material show different signal responses. Since it is extremely difficult to know the exact loose part material a-priori, an algorithm to estimate its material should be developed and integrated in the classification procedure.

Several classifiers have been implemented for damage monitoring in diverse applications including wavelet transforms (Eren & Devaney, 2004), statistical pattern recognition using outliers (Sohn, Allen, Worden, & Farrar, 2005), neural networks (Lee, Kirikera, Kang, Schulz, & Shanov, 2006), classifier ensemble (Banerjee, Safdarnejad, Udpa, & Udpa, 2016) and Hidden Markov Models (Zhou et al., 2007). Hidden Markov Models (HMM) have proven to be successful in several classification problems owing to their rich mathematical structure. Taking advantage of underlying Markov dynamics in its hidden states, they can successfully capture statistics of the damage response and aid in developing a reliable and effective SHM system. HMMs has been used in multi-fault diagnosis of rolling bearing joints (Purushotham, Narayanan, & Prasad, 2005) and ultrasonic inspection of cylindrical billets (Féron & Mohammad-Djafari, 2004). Apart from NDE, HMM has also been widely used for classification of images (Mouret, Solnon, & Wolf, 2009), speech recognition (Rabiner, 1989) and protein gene identification (Haussler & Eeckman, 1996). In this paper, HMM was used to classify ROIs from eddy current inspection signal into loose parts of different materials. The proposed algorithm implements a continuous Hidden Markov model by using phase information of the measurement signals. Section 2 covers the basic theory behind HMM and describes the classification algorithm based on HMM. In Section 3, implementation of this approach on classifying loose parts into two classes is presented. Performance of the proposed classifier model is compared with that of traditional Naive Bayes classifier and results are reported.

## 2. BACKGROUND

### 2.1. Theory of HMM

HMM is a statistical tool used for modelling sequential data (Rabiner, 1989). This approach comprises an observation sequence  $y = y_1, \dots, y_T$  of length  $T$  and a probability distribution

over  $y$  is defined by invoking a sequence of unobserved (hidden) discrete states  $x = x_1, \dots, x_N$ . The model implements (a) Markov dynamics on the sequence of hidden states, and (b) independence of the observations  $y$ , from all other variables, given  $x_n$ . In a Markov process, the probability of occurrence of a hidden state  $x_t$  at time  $t$  given all its prior states is completely dependent on the probability of occurrence of the previous state  $x_{t-1}$ , i.e.  $P(x_t | x_{t-1}, x_{t-2}, \dots, x_1) = P(x_t | x_{t-1})$ . These transition probabilities are defined in the initial state distribution vector  $\pi$  and the state transition matrix  $A$  in HMM. With  $N$  being number of states, HMM is parameterized by the  $N \times 1$  vector  $\pi$  whose  $i^{th}$  element is the probability  $p(x_1 = i)$  and the  $N \times N$  state-transition matrix  $A$  whose  $(i, j)^{th}$  element is  $P(x_{n+1} = j | x_n = i)$ . Additionally, HMM is described by a state-dependent observation density matrix  $B$  whose  $(j, n)^{th}$  element is  $b_j(y_n) = P(y_n | x_n = j)$ . Overall, the model parameters are denoted by  $\theta = \{\pi, A, B\}$ .

If the observations  $y = y_1, \dots, y_T$  are discrete and belong to the pre-defined set of alphabet  $V = V_1, \dots, V_K$ , then  $B$  reduces to a  $N \times K$  matrix whose  $(j, k)^{th}$  element is  $b_{jk} = P(y_n = V_k | x_n = j)$ . Such a model is known as a discrete HMM. Discrete HMM was first introduced in (Zhou et al., 2007) for damage classification. It served as a good classifier, but its performance reduced when features belonged to a continuous range due to loss of information during quantization. When observations lie in a continuous range, a continuous HMM is preferred where  $B$  can be modelled using a Gaussian mixture model (GMM) with  $M$  components, such that

$$b_j(y_n) = \sum_{m=1}^M c_m \mathcal{N}(y_n, \mu_{jm}, \Sigma_{jm}) \quad (1)$$

where  $c_m$ ,  $\mu_{jm}$ , and  $\Sigma_{jm}$  are the coefficients, mean, and covariance matrices respectively of the  $m^{th}$  mixture component (Gauvain & Lee, 1994).

### 2.2. HMM-Based Classification

In this paper, training dataset is used by the HMM to learn its model parameters. Given a 'training' observation sequence  $y$  belonging to one class, the maximum likelihood estimates of the HMM parameters are estimated for the classes using Baum-Welch algorithm (Seymore, McCallum, & Rosenfeld, 1999). The Baum-Welch algorithm was introduced as a special case of the expectation-maximization (EM) algorithm which iteratively maximizes the log-likelihood of the training data and obtains the optimum model parameters  $\theta$ . The details and derivation of Baum Welch algorithm can be found in (Bilmes et al., 1998). With intelligent selection of initial values, the model parameters are updated at  $(n + 1)^{th}$  iteration according to Equation 2.

$$\theta^{(n+1)} = \arg \max_{\theta} \sum_x p(x | y, \theta^n) \log p(x, y | \theta^n) \quad (2)$$

The EM algorithm is guaranteed to converge to the maximum of the likelihood function defined in Equation 3. Proof of convergence of the algorithm has been studied extensively by (Jordan & Xu, 1995) (Boyles, 1983).

$$\theta_{ML} = \arg \max_{\theta} \log p(y|\theta) \quad (3)$$

Training is repeated for obtaining HMM parameters for every class in the application. Once, maximum likelihood estimate of the HMM parameters are computed, the predictive likelihood of a ‘test’ observation sequence  $y'$  can be computed as:

$$\begin{aligned} p(y'|\theta_{ML}) &= \sum_x p(x, y'|\theta_{ML}) \\ &= \sum_x \pi_{x_1} \prod_{n=1}^{T-1} a_{x_n x_{n+1}} \prod_{n=1}^T b_{x_n y_n} \end{aligned} \quad (4)$$

Finally, classification is performed according to Bayesian rule and the ‘test’ observation is classified to the class having maximum predictive likelihood. Flowchart of HMM based classification algorithm is presented in Figure 1.

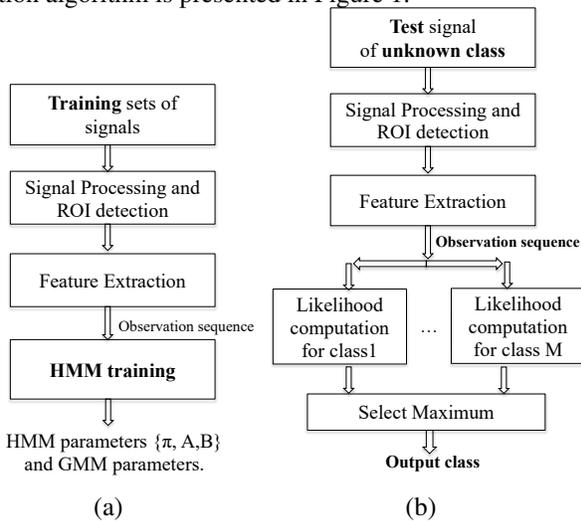


Figure 1. Algorithm design for HMM based classifier comprising (a) training for all classes and (b) classifying a test observation.

### 3. APPLICATION: FOREIGN OBJECT CLASSIFICATION

#### 3.1. Experimental Set-up and Data Collection

In this section, experimental data obtained from eddy current inspection of foreign objects outside steam generator tubes was analyzed. Figure 2 shows the experimental setup with associated eddy current inspection signal. A foreign object was placed outside the tube wall above tube support and an eddy current multi-frequency rotating probe collected data across the entire tube length. Eddy current measurements capture impedance changes caused by magnetic flux reduction and generate complex voltage at the output (De Mesquita,

Ting, Cabral, & Upadhyaya, 2004). Magnitude and phase information from the impedance plot distinguishes a loose part indication from background noise. A typical post processed eddy current inspection signal with the loose part indication is shown in Figure 2. It is obtained from SG tube inspection containing loose part made of carbon steel located 4mm above the tube support. In this experiment, data was collected from 88 SG tubes at three frequencies: 15KHz, 200KHz and 300KHz. Loose parts belonged to two categories of materials- copper and carbon steel.

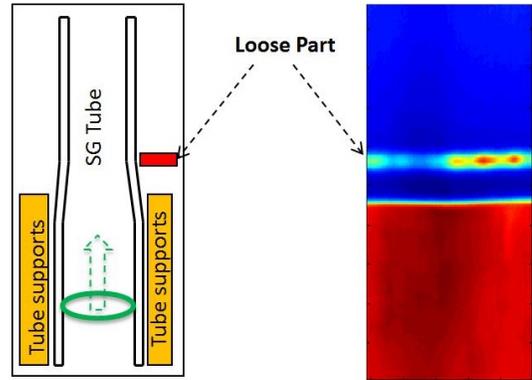


Figure 2. Experimental setup and eddy current inspection signal of SG tube at 15KHz with loose part indication.

Apart from material of loose part, factors which affect output signal response are size of the loose part and its position from the outer tube wall. A larger loose part located closer to the outer wall shows a stronger response in the measured signal than otherwise. To take these factors into consideration and make data more representative of real situations, this experiment was conducted with variable size of loose parts, located at different positions with respect to the tube wall. In this paper, 18 tube data with carbon steel loose parts and 19 tube data with copper loose parts, randomly chosen from the entire dataset, were used for training the proposed HMM based classifier for the two classes. The remaining 51 signals were used for testing the classification performance of developed classifier. In this study, it was desired to achieve high classification accuracy with limited training, replicating field inspection scenarios. Hence, fewer data were used for training compared to testing the classifier.

Figure 3a and 3b show the imaginary component of eddy current inspection signal of a section of SG tube with a loose part made of copper and carbon steel respectively lodged outside the tube wall. The axial length of the tube described by the ordinate is 80mm whereas the abscissa correspond to 360° circumferential span of the tube. The rectangular box indicates the location of the loose part at the three frequencies-15 KHz (low), 100 KHz (medium), 300 KHz (high). A useful method for representing and comparing eddy current analysis results is by studying the corresponding Lissajous curves

(Jarmulak, 1997) where the output signal from ECT is plotted in a complex plane. Roughly, the amplitude of the curve corresponds to volume of the defect and its phase corresponds to defect depth and location. The Lissajous plots for copper and carbon steel loose part detection are shown in Figure 4a and 4b. The  $x$  and  $y$  axes describe the real and imaginary components respectively in volts. It is noted that the output signal response varies for the two materials. For carbon steel, loose part indications at 15KHz have signal at higher voltage than background noise whereas for copper, signals at a voltage lower than surrounding noise identifies the loose part. Without information about the material, automated analysis software is typically unable to determine whether to retain signal above or below a threshold as the potential loose part region. Thus an algorithm is required to classify the material of the loose part signal before applying proper thresholds and locating the loose part.

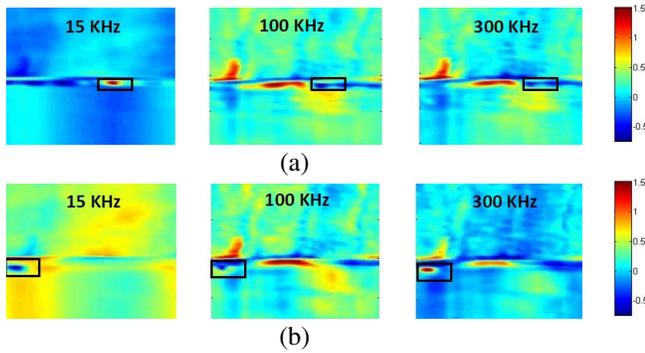


Figure 3. Imaginary component of eddy current response signal for (a) carbon steel loose part and (b) copper loose part at three frequencies.

### 3.2. Choice of Model Parameters

The primary feature that is used to detect a loose part signal from its background noise is phase of the complex eddy current post-processed signal response. Using magnitude thresholds, signals with higher amplitude are selected as ROIs containing potential loose parts and rest of signal is discarded. According to principle of eddy current testing, phase of a loose part signal is typically different from that of noise. Therefore with proper phase thresholds, ROIs containing loose part signals is separated from noise indications which are retained even after magnitude thresholding.

However, phase information of signal at only one frequency channel is not sufficient for distinguishing loose part signals of two different materials. In lieu of single frequency response, loose part signals of copper and carbon steel can be distinguished by analysing their phase over a range of frequencies. From Figure 3 and Figure 4 it was observed that the phase of the ROIs follows a trend over the frequency range such that phase at a particular frequency depends on its value

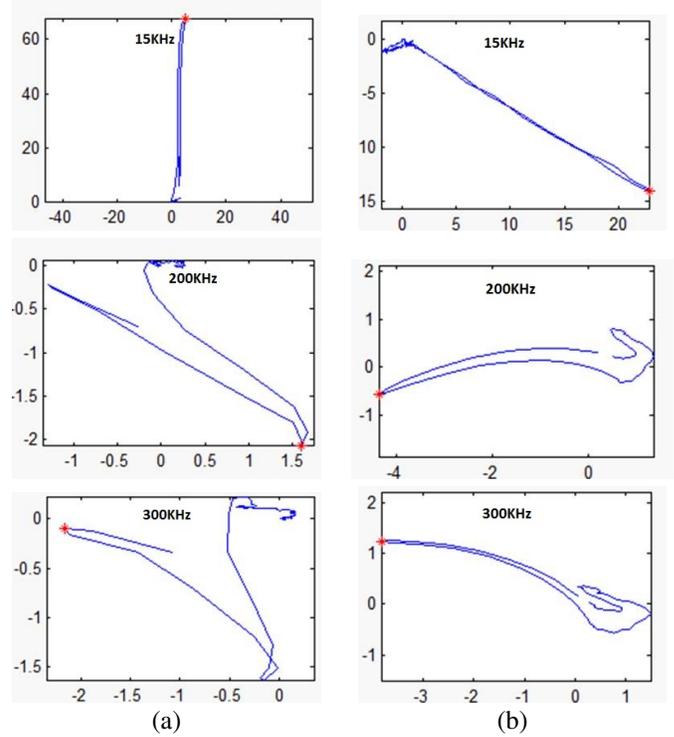


Figure 4. Lissajous plots for loose part indications made of (a) carbon steel (b) copper.

in the previous frequency channel. This forms the motivation behind exploiting the underlying Markovian dynamics. HMM models the temporal transitions between the three frequency channels in conjunction with the associated observation statistics and hence HMM based classifier was found to be suitable for classifying loose part inspection data into two classes of materials.

### 3.3. Naive Bayes Classification

In this study, the ‘training’ dataset consisting of phase at three frequencies for 37 datafiles was used to model Naive Bayes classifier for comparing classification performance of proposed HMM-based classifier (Rish, 2001). Naive Bayes classifier computes the Bayes posterior probability for all classes and labels it onto the class with the highest posterior probability measure. It is an optimal classifier for a two-class classification task and has been widely used for damage detection in engineering materials (Addin, Sapuan, Mahdi, & Othman, 2007) and prognostic applications by eddy current analysis (Qiu et al., 2013). The confusion matrix based on the classification result on the ‘test’ dataset consisting of 51 measurements is reported in Table 1.

Correct classification rate, i.e (No. of correct classifications) / (Total no. of samples)  $\times 100\%$  was calculated as 72.54 % and almost half of carbon steel loose part data were misclassified by the Naive Bayes classifier. The phase information at the

Table 1. Confusion matrix for Naive Bayes classification of loose part material.

$c \backslash \hat{c}$	Carbon Steel	Copper
Carbon Steel	14	13
Copper	1	23

three frequencies were not discriminative of the two classes of loose part materials resulting in poor performance of the classifier.

**3.4. HMM-Based Classification**

The dependency graph for HMM in this application is shown in the Figure 5. The frequencies are chosen as the hidden states  $S_0, S_1, S_2$  whereas the phase values corresponding to the frequency channels are considered as the observation variables  $O_0, O_1, O_2$ .

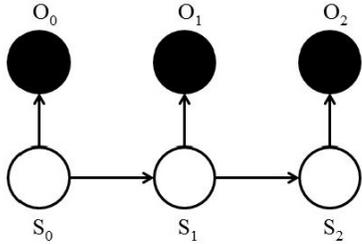


Figure 5. Dependency graph of HMM for classification of loose part data.

Since phase of signals after magnitude thresholding lies in the continuous range within 0 to 360°, the proposed classifier is based on continuous HMM where the B-matrix is estimated using a Gaussian mixture model (GMM). The number of components in the GMM is selected according to the number of clusters formed by K-means approach in the 3-dimensional feature space of the two classes (Hartigan & Wong, 1979). As shown in Figure 6, for both carbon steel and copper, phase at the three frequencies form two separate clusters and therefore for this dataset, a mixture of 2 Gaussian functions was chosen. The estimated means and covariances of the GMM, computed by K-means clustering, were used to model the observation matrix.

An interesting thing to note is that features from two materials are not separable in the feature space which was the primary reason behind the poor classification performance of the Naive Bayes classifier. This reinforces the benefit of the HMM based classifier which is able to exploit the underlying Markovian dynamics of signals and classify loose parts with different material properties. Besides, copper loose part shows more distinct indications on the eddy current response signal as compared to carbon steel due to characteristic dif-

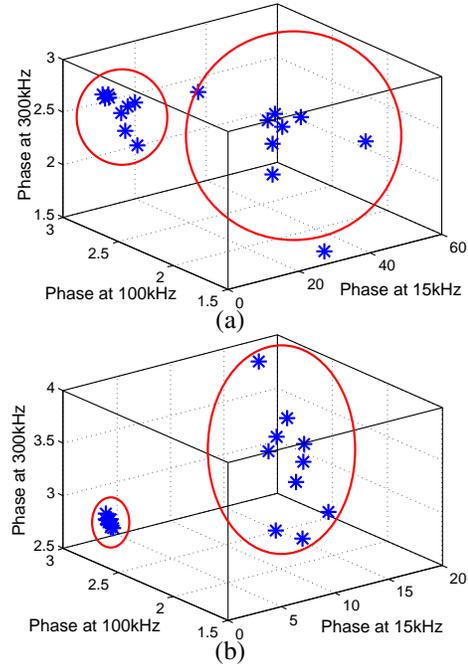


Figure 6. Feature space for (a) carbon steel (b) copper.

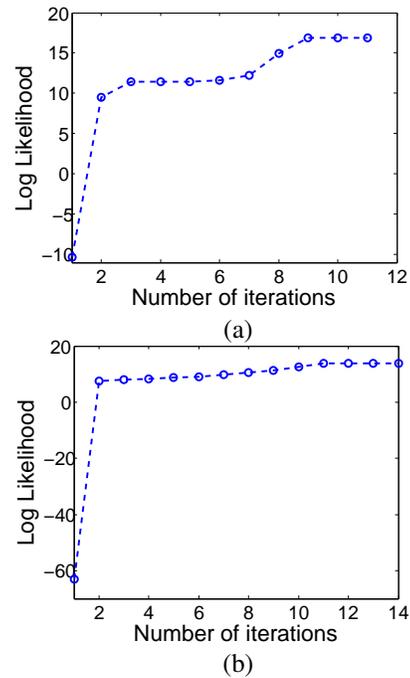


Figure 7. Plot of log-likelihood function in Baum Welch algorithm for (a) carbon steel and (b) copper.

ference of its material properties from inconel, hence copper data formed a tighter cluster in the feature space.

During training with 37 loose part data according to the Baum Welch algorithm, the logarithm of the likelihood function at every iteration was evaluated and plotted in Figure 7 for car-

bon steel and copper. For both the cases, the log likelihood increases with every iteration till it converges to the maximum likelihood parameters of the HMM.

To illustrate the performance of the HMM classifier, 51 test samples, 27 with carbon steel loose part and 24 with copper loose part, were classified by the trained algorithm. The correct classification rate was calculated as 88.24%. The associated confusion matrix is recorded in Table 2.

Table 2. Confusion matrix for HMM-based classification of loose part material.

$c \backslash \hat{c}$	Carbon Steel	Copper
Carbon Steel	23	4
Copper	2	22

#### 4. CONCLUSION AND FUTURE WORK

This paper demonstrates the benefit of Hidden Markov Models for characterizing the material of loose part before applying selective signal processing on the eddy current data. Most loose part materials were classified correctly by the HMM based classifier using phase information as classification features. Further, by using continuous HMM instead of its discrete version, the quantization step and its associated errors was avoided. By taking advantage of underlying Markovian principle, the proposed classifier exhibits better classification performance compared to traditional Naive Bayes. Extension to more types of loose part materials other than copper and carbon steel will be studied in future in order to verify the robustness and classification capability of the proposed method.

In this study, the initial values of the HMM parameters were chosen randomly for obtaining the maximum likelihood estimate by Baum Welch algorithm. A wrong selection of the initial values may result in sub-optimum parameter estimates as the EM algorithm can get trapped in a local maxima which can degrade the performance of the proposed classifier. In order to avoid local maxima of the likelihood, a simulated annealing scheme can be employed. Moreover, the dataset studied in this application was assumed to adhere to Gaussian mixture model which may not be true for other applications. In such cases, non-parametric approaches should be preferred.

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