Program Digest, 2019 IEEE International Ultrasonics Symposium (IUS)
Glasgow, Scotland, October 6-9, 2019

Unsupervised Machine Learning for Ultrasonic Flaw Detection using Gaussian Mixture Modeling, K-Means Clustering and Mean Shift Clustering

Kushal Virupakshappa
Dept. of Electrical and Computer Engineering
Illinois Institute of Technology
Chicago, USA
kvirupak@hawk.iit.edu

Erdal Oruklu
Dept. of Electrical and Computer Engineering
Illinois Institute of Technology
Chicago, USA
oruklu@iit.edu

***Abstract*—Supervised Machine Learning (ML) algorithms such as Neural Networks, Support Vector Machines and Logistic Regression have been successfully utilized in Ultrasonic Non-Destructive Evaluation (NDE) applications. In supervised learning algorithms, data outputs are labeled and classified for training. In contrast, Unsupervised Machine Learning (UML) algorithms identify and exploit the commonalities in the data and no "ground truth" is necessary. In this work, we use three different UML algorithms based on K-means clustering, Gaussian Mixture Modeling and Mean Shift Clustering in order to detect and locate flaw echoes in ultrasonic A-Scan data. All three algorithms have been shown to perform flaw classification successfully. In particular, Gaussian Mixture Modeling achieves highest detection accuracy at 93%.**

***Key Words*—Discrete Wavelet Transform(DWT), K-means Clustering, Gaussian Mixture Modeling (GMM) and Mean Shift Clustering.**

I. Introduction

Detection of flaw/void/deformity is critical in many applications related to structural analysis and Non-Destructive Evaluation (NDE). In recent years, Machine Learning methods have been successfully employed to enhance the detection capability/accuracy. Several Supervised Machine Learning implementations for NDE applications can be seen in [1], [2] and [3]. Unsupervised Machine Learning methods also have been used in [4], [5] and [6] for detection. In [4] Time of Flight Diffraction (TOFD) data is used to classify weld defect using K-means clustering and K-nearest neighbor algorithm while in [5] it is used to classify radar signal for inspecting concrete structure. Finally in [6], a review of ultrasonic imaging and clustering methods in order to detect cracks in concrete is presented. UML methods have lower computational requirements and they are well-suited for real-time embedded implementations.

In this research, we conduct a comparative study on the performance of classical unsupervised machine learning algorithms. The algorithms chosen are the classical K-means clustering, Gaussian Mixture Modeling (GMM) and Mean Shift Clustering. K-means clustering is a well-known method to find the defined number of centroids from a given set of data. Since the objective here is to find the location of the flaw echoes, two clusters are defined: one representing grain noise and the other representing flaw. Another closely related, probabilistic model is the Gaussian Mixture Modeling (GMM). In this algorithm not only the centroids of the cluster but the variance is also considered as a parameter. Third UML algorithm uses Mean Shift Clustering which is a hierarchical clustering method in which the number of clusters are not specified by the designer; whereas in K-means and GMM the designer must specify the number of clusters.

This paper is organized as follows: Section II gives an overview of the input feature selection and Section III briefly describes the UML algorithms that are used in this work. In Section IV, the software pipeline is discussed with an interpretation of algorithm. Experimental results and performance figures are shown in V.

II. Feature Selection

The A-scan data obtained from non-destructive testing experiments usually contain noise embedded within (system noise and the grain noise). Depending on the sensitivity and the central frequency of the transducer used, the grain noise may be pretty significant. This makes flaw detection task very challenging. As a preprocessing step, the A-scan is subjected to two levels of Discrete Wavelet Transform (DWT) decomposition. Since the Low-pass, Low-pass (LL) component of the DWT has distinguishable signal-to-noise ratio, the LL component of the DWT decomposition is chosen as the input feature for UML models [7], [8].

The LL component [7] cannot be directly used as the distribution of the signal is concentric as shown in the Scatter Plot in Fig.1. In Fig. 1 the red dots indicates data points for flaw cases and blue dot indicates the data points for no flaw cases for a window size of 4. The plot is one window sample against the other window sample. Therefore, power signal of the LL component is chosen as it can seperate the signals which help in clustering for detection (See Fig. 2).

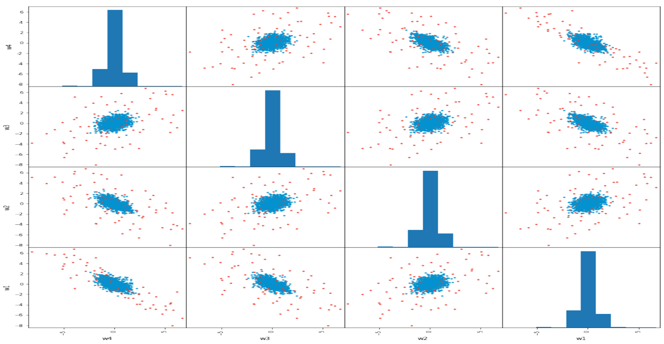

Fig. 1. Scatter Plot of LL component of A-scan.

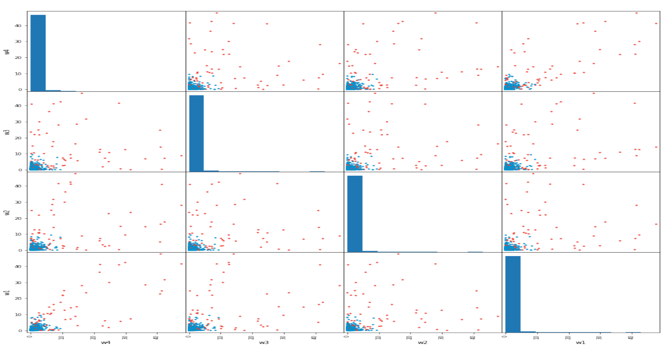

Fig. 2. Scatter Plot of Power of LL component DWT signal.

III. Overview of UML Algorithms

In this section, a brief overview of the algorithms is presented.

A. K-means Clustering

K-means clustering involves dividing the given data set into K-groups and is accomplished by initially assigning random centroids for each cluster and then each data point is assigned to a specific cluster and then the centroid is updated. The only parameter that controls the assignment of cluster is the centroid. Algorithm steps are:
Given a new data point for classification, find the closest centroid and assign the related cluster number the data point.

This algorithm has been chosen for classification since it is the simplest algorithm with only centroid as the parameter to define each cluster.

B. Gaussian Mixture Modeling

Gaussian Mixture Modeling divides a given data set into K-number of clusters depending on the parameters including prior probability, mean and variance of each cluster. Each of these parameters are determined by Expectation Maximization algorithm. Algorithm steps are:
Given a new data point, the probability that it belongs to a particular cluster is computed and the data point is assigned to the cluster with highest probability.

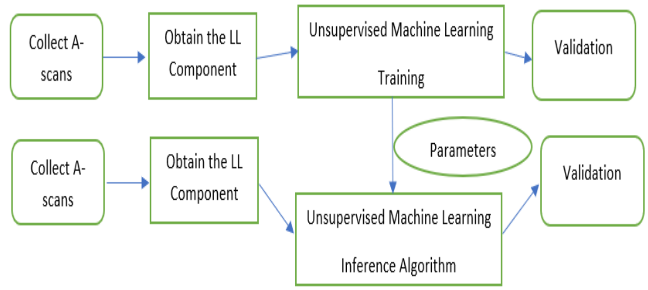

Fig. 3. Software pipeline for training and testing.

The signals related to Ultrasound NDT A-scans have Rician Distribution and as an approximation, the distribution can be approximated to Gaussian distribution (after mean shift to random variable zero during pre-processing stages).

C. Mean Shift Clustering

Mean Shift Clustering works on the Kernel Density Estimation algorithm. In Kernel Density Estimation algorithm, each data point is assigned a distribution and the distribution function is updated until the required number of clusters are achieved.

The assignment of cluster to a test samples is done by computing the probability that the given sample might belong to that cluster and is assigned the cluster with highest probability. The reason for choosing this algorithm is that the it supports Gaussian Distribution.

IV. Implementation

The general software pipeline that has been used in this work is as shown in Fig. 3. The training pipeline includes processing A-scans and obtaining the LL component of the DWT decomposition. These training samples are split into batches for training and validation. The parameters of training are obtained for each algorithm and stored. Validation step gives a preliminary view on how the algorithms are doing. The preliminary validation accuracy for K-means clustering is between 85% and 91%. For Mean Shift Clustering and Gaussian Mixture Modeling validation accuracy varying between 88% and 93% was observed.

V. Results

During optimization, the number of sample A-scans used for K-means clustering and GMM are 100 each while the number of sample A-scans used for Mean Shift clustering are 50. The reason being both K-means and GMM take $O(t*k*n)$ time for execution while Mean Shift clustering takes $O(t*n^2)$. The K-means and GMM had a MSE of 3 with a variance of 1 for a window size of 5 while Mean Shift clustering needed

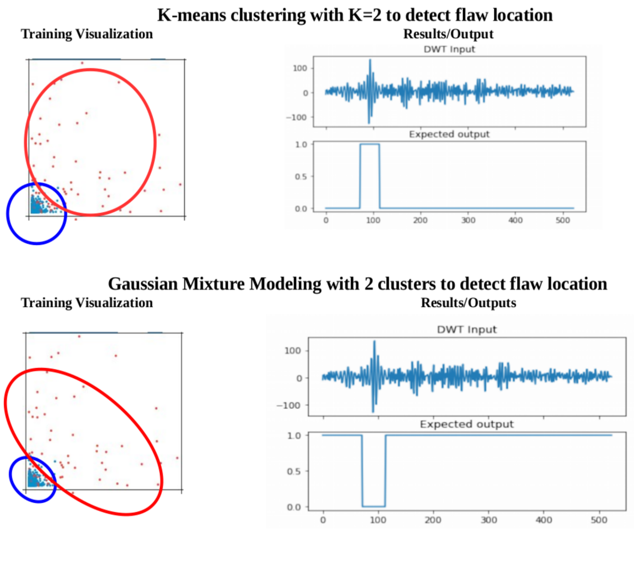

Fig. 4. K-means Clustering and Gaussian Mixture Modeling

a window size greater than 15 with MSE of 3. Sample results with experimental data are shown in Fig. 4.

The confusion matrix for GMM based detection is shown in the Table I. It had an average accuracy of 93%.

The average accuracy of all the three algorithms that were tested in this work are tabulated in Table II. The number of clusters used in all the three cases were two.

TABLE I
CONFUSION MATRIX FOR GMM

n=125	Predicted: Flaw	Predicted: No Flaw
Actual: Flaw	TP=93%	TN= 7%
Actual: NO Flaw	FP=6%	FN= 94%

TABLE II
CONFUSION MATRIX FOR GMM

Algorithm	Average Accuracy
GMM	93%
Mean Shift Clustering	93%
K-means Clustering	89%

VI. CONCLUSION

This work demonstrates that clustering algorithms can be used to classify the scenario of flaw / no-flaw classification. GMM and Mean Shift Clustering tend to have an upper hand but the optimization of parameters take significantly longer time than K-means clustering. The inference signals did indicate an inherent time lag in detection which is not a setback for our application of binary classification. This can be avoided by bringing in fixed amount of latency for hardware implementation. Since the number of parameters are smaller and the inference algorithms are less complex, the implementation of the UML algorithm on an embedded platform (such as an FPGA) can be considered as future implementation.

VII. ACKNOWLEDGMENT

Authors gratefully acknowledge the support of NVIDIA Corporation for the donation of the GPU hardware and software tools used in this research.

REFERENCES

[1] F. W. Margrave, K. Rigas, D. A. Bradley and P. Barrowcliffed, 'The use of neural networks in ultrasonic flaw detection,' Measurement,Vol. 25, No. 2, March 1999, Pages 143-154.

[2] Y. Huang, D. Wu, Z. Zhang, H. Chen and S. Chen, 'EMD-based pulsed TIG welding process porosity defect detection and defect diagnosis using GA-SVM,' Journal of Materials Processing Technology,Vol. 239, January 2017, Pages 92-102.

[3] J. Saniie, E. Oruklu and S. Yoon, 'System-on-chip design for ultrasonic target detection using split-spectrum processing and neural networks,' IEEE transactions on ultrasonics, ferroelectrics, and frequency control, Vol. 59, No. 7, pp. 1354-1368, 2012.

[4] R. H. F. Murta, F. A. Vieira, Victor O. Santos, and E. P. de Moura, 'Welding Defect Classification from Simulated Ultrasonic Signals,' Journal of Nondestructive Evaluation, September 2018.

[5] T. P. Sattar, M.O.F. Howlader and S. Dudley, 'Development of a Wall Climbing Robotic Ground Penetrating Radar System for Inspection of Vertical Concrete Structures,' International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering, Vol 10, No. 8, pp. 1346-1352.

[6] A. Mohan and S. Poobal, 'Crack detection using image processing: A critical review and analysis,' Alexandria Engineering Journal, Vol. 57, No. 2, June 2018, Pages 787-798.

[7] K. Virupakshappa, M. Marino and E. Oruklu, 'A Multi-Resolution Convolutional Neural Network Architecture for Ultrasonic Flaw Detection,' 2018 IEEE International Ultrasonics Symposium (IUS),22-25 October 2018.

[8] M. Marino, K. Virupakshappa and E. Oruklu, 'A Recurrent Neural Network Classifier for Ultrasonic NDE Applications,' 2018 IEEE International Ultrasonics Symposium (IUS), 22-25 Oct. 2018.