A machine learning approach for classification tasks of ECT signals in steam generator tubes nearby support plate

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Abstract. An automatic classification relying on model based machine learning approach is proposed in the context of steam generator tubes inspection by means of eddy current testing. Such tool could realize a first selection of problematic areas and thus potentially considerably reduce the amount of data experts need to analyse. After the generation of databases of signals covering the configurations of interest, a set of classifiers are trained and compared in terms of performance. In order to mitigate the size of datasets and enhance classification performance, a classical dimensionality reduction technique. Results indicate a good potential of such methods for assisting human experts in the task of ECT signals analysis.

INTRODUCTION

Automated analysis of nondestructive testing signals is a important issue in many applications, where large amounts of data are generated. In a manufacturing context, for instance, such analysis can provide useful indicators to monitor the effects of manufacturing parameters. In this communication, we focus on a important application of eddy current testing (ECT) in the field of Energy: the inspection of steam generator (SG) tubes equipping nuclear power plants. These tubes that are regularly inspected from the inside using ECT probes, in view of detecting and characterizing flaws that could potentially lead to a tube breaking. Such an event would cause contamination of the secondary water circuit by water coming from the primary one, which has to be avoided. As a single steam generator contains several thousands of tubes, the amount of data that need to be analysed by experts is very large, even when using conventional bobbin probes or rotating ones like the Pluspoint probe or the french probes *Sonde Tournante Transverse* (STL) and *Sonde tournante Longue* (STL), which are all operated at several frequencies. If now we consider inspections with array probes like the SMX one (adaptation of the X-probe to the french context), which are made of about 30 coils, then the analysis becomes even more challenging.

Machine learning (ML) techniques can prove useful in order to support the manual analysis of kilometres of recorded signals, as they are able to detect suspicious patterns in data, provided that they have been trained properly. It has to be noted here that the problem to be addressed is not easy: flaws are mainly appearing in parts of the steam generator tubes, where support plates are guiding them from the outside or in bended areas near anti-vibration bars. For these reasons, flaws signals are often mixed with other ones coming from the support plate itself or from some clogging occurring in the area separating the tube and the support plate. As fast models tools able to take account for industrial probes and complex interactions mentioned before are available in the CIVA platform, dedicated to simulation for nondestructive testing, it will be used intensively to train the ML classifiers used in this work. The classifiers implementation is that of the excellent Scikit Learn toolkit [1]. This paper is structured as follows. First, the application case is presented and the objectives in terms of classification are detailed. Then, Dimensionality reduction techniques applied and the classification algorithms used are discussed. Finally, results are presented and compared in terms of performance.

APPLICATION CASE: SG TUBES INSPECTION WITH A BOBBIN COIL

The case of interest in this work is the detection of a flaw affecting a SG tube in the region located under a plain support plate. The tube itself is made of Inconel 690 alloy (non magnetic), has a conductivity of 1 MS m^{-1} and inner and outer radii of 9.84 mm and 11.11 mm, respectively. The support plate is made of magnetic steel (conductivity: 1.43 MS m^{-1}, relative permeability: 50) and has a width of 20 mm and a thickness that is sufficiently large, so that the probe is not influenced by its external radius. The deposit located in between the tube and the support plate is made of copper (non magnetic, conductivity: 56 MS m^{-1}) and is always starting at the edge of the support plate, which is generally the case in a situation where some clogging appears. One should note, though, that the choice of deposit conductivity is not realistic here, as such deposits are generally made of mud containing metallic particles. However, such a high deposit conductivity is used as a limit case, where the flaw signal is quite low with respect to the deposit one. The probe use for inspection is a standard bobbin coil made of two identical axial coils with inner/outer radii of 7.83 mm and 8.5 mm, respectively, a height of 2 mm and 70 turns. They are separated by a gap of 0.5 mm along the tube axis. The flaw, when it is present is always an outer groove. The objective of the classification is to distinguish between three situations, depicted in Figure 1.

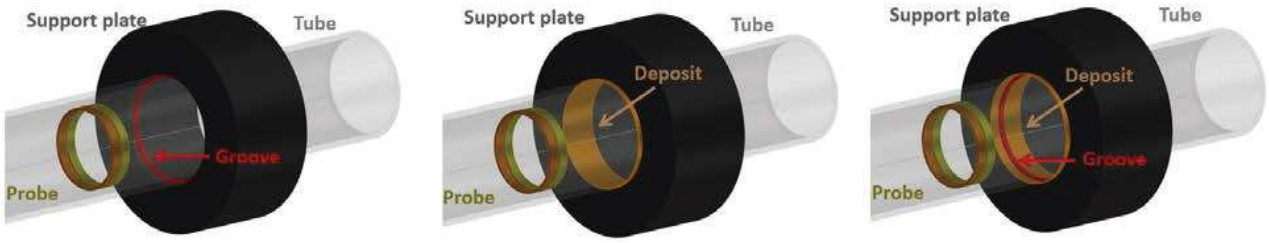


FIGURE 1. Configurations of interest: presence of a groove without deposit (left), presence of deposit without groove (center) and presence of both deposit and groove (right).

In addition to the constant parameters detailed above, five parameters are considered as variables and will constitute the dimensions of the signal databases that will be generated for training and testing the classifiers. Those parameters, as well as their range of variation, are listed in Table 1.

TABLE 1. Variable parameters with their range of variation in millimeters.

Parameter	Range
Deposit thickness	[0.01, 0.2]
Deposit length	[2, 10]
Groove length	[0.5, 2.0]
Groove height	[0.127, 0.762]
Groove z-position	[65.5, 75]

Numerical Solver Used for Simulation

This simplified configuration can be modelled using a 2D numerical code with rotational symmetry. In the present work, a code based on the Finite Integration Technique (FIT) [2] and embedded in the CIVA software is used to carry out the simulations. In finite integration technique (FIT) classical formulation, Maxwell's equations are discretised using a pair of mutually orthogonal, staggered grids, referred to as primary G and dual grid $\tilde{G}$, respectively. In the harmonic regime and assuming linear materials, the FIT quasi-static formulation for the magnetic vector potential $\mathbf{a}$ reads:

$$\tilde{\mathbf{C}}\mathbf{M}_{\nu}\mathbf{C}\mathbf{a} + j\omega\mathbf{M}_{\kappa}\mathbf{a} = \mathbf{j}, \tag{1}$$

where $\mathbf{a}$ and $\mathbf{j}$ are column vectors containing the magnetic potential line integrals along the primary grid edges and the excitation current fluxes through the dual grid facets, respectively, and ω is the angular frequency. The $\mathbf{C}$, $\tilde{\mathbf{C}}$ matrices

stand for the curl operator in the discrete space defined by the primary and dual grid, respectively, interrelated by the duality property $\tilde{\mathbf{C}} = \mathbf{C}^T$. The diagonal matrices $\mathbf{M}_\nu$ and $\mathbf{M}_\kappa$ are the reluctivity and conductivity matrices obtained by the discretisation of the constitutive relations.

Once (4) is solved, the solution for the electric grid voltages **e** and the magnetic grid fluxes **b** are obtained using the relations

$$\mathbf{e} = -j\omega\mathbf{a} \tag{2}$$

$$\mathbf{b} = \mathbf{C}\mathbf{a}, \tag{3}$$

in analogy with the continuous case. Note that the scalar potential term has been omitted from (2) since in the quasi-static formulation it accounts for the static terms. Finally, the ECT signal (in Volts) is derived after the calculation of both impedances Z_1 and Z_2, corresponding to each coil, for each position of the probe scan:

$$ECT_{sig} = (Z_1 - Z_2)\, I, \tag{4}$$

where I is the constant injection current. Note that contributions of mutual impedances Z_{12} and Z_{21} to the ECT signal are cancelling in this particular case, as the probe is modelled in differential mode.

DATA PROCESSING AND CLASSIFICATION TOOLS

The setup of a proper classification tool for our problem can be divided in three successive steps, namely the generation of a training set, as we are here working with synthetic data only, a dimensionality reduction step and finally the selection of the classification algorithm.

Generation of the Training Set

Following a so-called supervised classification approach, the classifier has to be trained with a dataset made of ECT signals and the category they belong to. This dataset should be as representative as possible of the investigated space of parameters variations, in order to get a high accuracy of the classification. But it should also, in our case, be not too large so that it can be generated with a reasonable computation time. Convenient choices for the sampling of input parameters are design of experiments like full grids (too expensive), or pseudo random sequences like Sobol or Halton sequences or latin hypercube samplings. their main advantage is that the inputs samples to be evaluated with the model are generated once and for all, so that the costly part of model evaluations can be carried out in a parallel way. Its main drawback is its sub-optimality in terms of number of samples and samples repartition with respect to the behaviour of the physical signals. Alternatively, adaptive sampling strategy can prove much more efficient as they take the model behaviour into consideration, but they necessarily imply (at least partly for the most recent versions) an iterative and sequential process [3]. In this work, a mixture of full grid and latin hypercube sampling was used to generate the training set.

Dimensionality reduction

It is commonly observed that training classifiers with respect to raw signals may either lead to poor performance [4], or require an exponentially increasing number of samples in the training set. To mitigate this effect, known as curse of dimensionality, an intermediate step consisting in reducing the number of dimensions may be introduced. After such a transformation, the classifier does not learn the link between raw signal and categories anymore, but instead focuses on a reduced set of descriptors, chosen so that they convey most of the information contained in the physical signals. In this work, quite classical projections based on Principal Component Analysis (PCA) and the Kernel Principal Component Analysis (KPCA), which represents PCA non linear counterpart. A sketch of the procedure employed to perform feature extraction is given in Figure 2. For visualization purpose, the projected space is three-dimensional in the picture, but the projected space used in the study was actually of dimension 10.

Readers interested by supervised feature extraction methods applied to ECT inspection signals, we shall refer to the recent papers [5] [6] where partial least squares method was applied as a preliminary stage before preforming regression tasks.

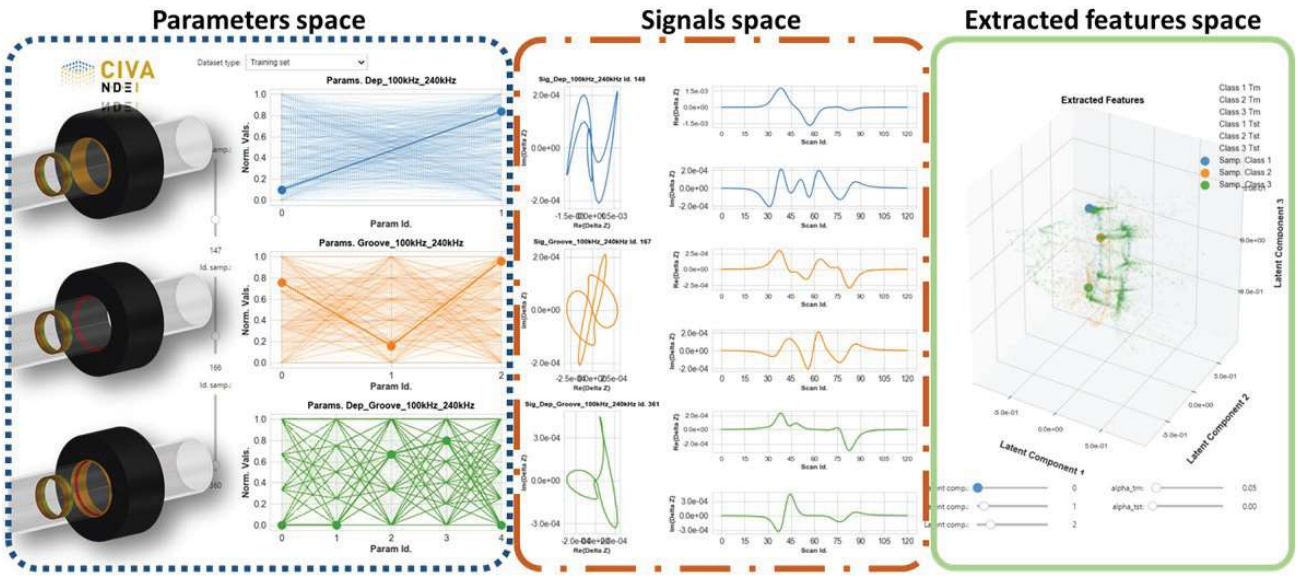


FIGURE 2. Overview of the dimensionality reduction pipeline applied to ECT inspection of SG tubes. Encircled by a braked line ('-'), three plots showing the set of parameters considered for three different inspection cases where each solid line within the three plots correspond to the set of chosen input parameters. Within the solid dotted line ('– -') frame, we see corresponding ECT signals associated to the three different inspection test cases considered. Finally, the last plot corresponds to the whole set of ECT signals projected into the 3D extracted feature space. Each ECT signal corresponds to a point in this space.

Selection of the classification algorithm

Since one of the purposes of this paper consists in presenting a general framework for ML based classification algorithms applied to ECT signals, we have considered five different classifiers, which are based on different principles. Those are Naive Bayes (NB), K-Nearest Neighbors (KNN) classifier, Multi-Layer Perceptron for Classifier (MLPC) and Support Vector Classifiers (SVC). A brief overview of each of them is provided below.

Naive Bayes classifiers

Naive Bayes [7] can be considered an "entry-level" approach for classification due to its algorithmic simplicity. For this reason it can be considered a very nice tool to provide a kind of average level classifiers in terms of accuracy. NB algorithm works with labeled data and employs the Bayes' theorem postulating the statistical independence between features pairs. This means that in case of multiple-classes problems, each class can be treated with its own distribution independently from the others, mitigating in this way the curse of dimensionality. This is also the main reason why NB classifiers are quite simple to train with a small amount of data. As a consequence, both training and test phases can be much faster than with other classifiers described hereafter. The payback of NB classifiers consist in lack of accuracy in the prediction of probabilities associated to the classification results.

K-nearest neighbours classifiers

K-nearest neighbours classifiers [4], instead of aiming at the construction of a general classification model, tries to perform classification by aggregating together the different classes contained within the training set just by averaging the set of K neighbors around a provided instance within the training set. The averaging mechanism is normally performed via majority vote. Even though the KNN performance may degenerate due to the curse of dimensionality, when properly trained, it represents a robust choice to perform classifications. In this paper, the most suitable number of neighborhood has been chosen via a cross validation stage before performing predictions.

Multi-layer perceptron classifiers

Multi-layer perceptron classifiers is a supervised learning method that applies the multi-layer perceptron neural network paradigm [8] to classification tasks. It is worth mentioning that the MLPC version employed in this paper exploits the back-propagation algorithm. One of the most desirable features of MLPC algorithm is its ability to learn non-linear relationships between inputs and targets of the training set. Non linearity can be properly described by tuning the number of non-linear multiple layers, i.e., the hidden layers enclosed between input and output layers. Such a flexibility is paid for in terms of numbers of parameters to tune in the algorithm. Moreover, the fitting procedure partially depends on the weights considered within the initialization neural network initialization stage. In this paper, cross-validation stage has been used in to select the regularization parameter α of the algorithm.

Support vector classifiers

Support vector machines are a very popular set of algorithms in the ML community. Their main strength is the capacity to provide predictions based on a reduced set of training data, called support vectors. This turns into a sparse and thus "lighter" model compared to the previously described MLPC. Moreover, from the mathematical point of view, SVC formulation rely on a solid statistical learning theory [9], which provides a somewhat "intuitive" interpretation of how training and prediction results are produced, as a statistical and physical meaning is given to SVC hyper-parameters. In this work, we fit the set of SVC hyper-parameters via a classical grid-based cross-validation stage.

Major voting classifiers

Major voting classifiers belongs to the branch of classification algorithms that are known under the name of ensemble learning algorithms. The purpose of those algorithms is to train a so-called strong classifiers by combining the contributions of a set of so-called weak classifiers. Different variants of ensemble learning methods have been developed in the last two decades by the ML community [10]. In this paper, we focused on the major voting algorithm, which consists in the weighted contribution of different classifiers (KNN, MLPC and SVC in our case).

RESULTS OBTAINED ON SYNTHETIC DATA

Following the methodology previously described, a synthetic training set has been generated by means of a large simulation campaign with the ECT module of the CIVA software [11]and corresponding to the three different configurations (i.e., Classes 1, 2 and 3) presented in Figure 1. Deposit and groove parameters have been chosen such that deposit thickness was ranging from 0.01 mm up to 0.02 mm, whereas the deposit length considered was enclosed in the range from 2.0 mm up to 10 mm. The groove length is enclosed within the interval from 0.5 mm up to 2.0 mm and the smallest groove height was set to 0.127 mm whereas the larger one was 0.762 mm. Finally, groove z-position spans the interval from 65.5 mm up to 75.0 mm, which corresponds to the zone underneath the support plate, which potentially hosts the deposit. Three datasets (one per class) of 350, 370 and 2650 samples have been generated based on a mixed full factorial, Latin Hyper-cube Sampling (LHS) design and put together to constitute the training set. The test sets was generated by simulating 250 LHS samples for each class with the CIVA software. Furthermore, due to the rotational symmetry of the considered inspection problem, a linear scan having 120 points encompassing both the support plate sides was considered. In order to enhance the performance of the classification process, we projected the whole set of measurements onto the extracted feature space by employing alternatively PCA or KPCA methods. Considering PCA, the suitable number of extracted features was established targeting a projection stage from which we were able to retrieve 99% of the explained variance [4] of the training set. The results of this choice was that a ten dimensional extracted feature space was obtained. In order to fairly compare the performance of KPCA against its linear counterpart, the same number of dimensions was used for this projection method.

The fitting procedure of classifiers presented above was performed by employing a 5-fold cross-validation stage, which has led to the estimation of the regularization parameter α in MLPC and of the regularization parameter c and the Gaussian kernel parameter γ for SVC. Concerning KNN classification algorithm, the best number of neighbours and the leaf size were obtained also via cross-validation procedure. The naive Bayes classification algorithm employed in this work assumed to deals with Gaussian likelihood function. Finally, major voting algorithm exploited the previously trained MLPC, SVC and KNN classifiers.

Looking at results shown in Figure 3, one can readily notice that SVC algorithm performs better than the naive Bayes, KNN and MLPC, as it provides higher accuracy in the challenging task of discriminating between Class 1 and

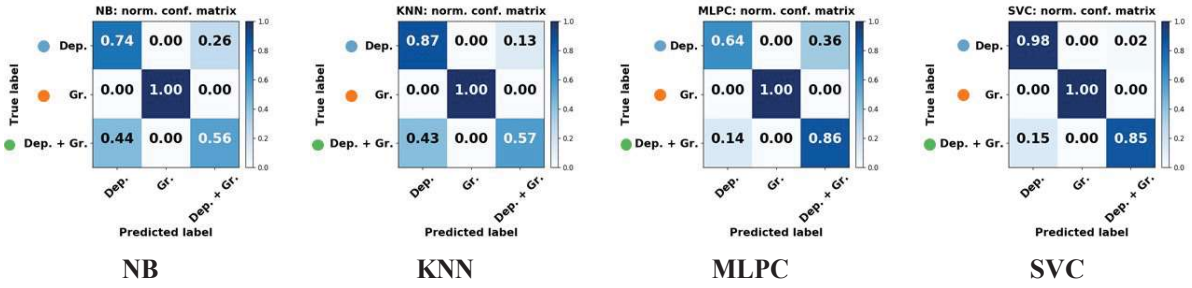


FIGURE 3. Classification results based on PCA feature extraction provided by the different classifiers are synthesized using normalized confusion matrices.

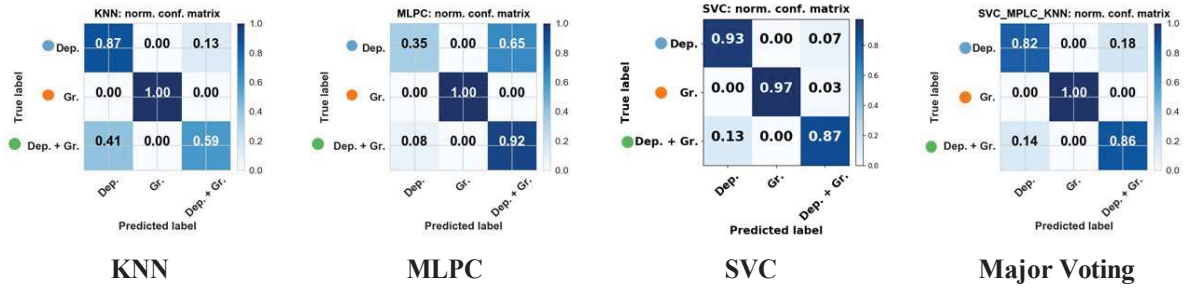


FIGURE 4. Classification results based on KPCA feature extraction provided by different classifiers are synthesized using normalized confusion matrices.

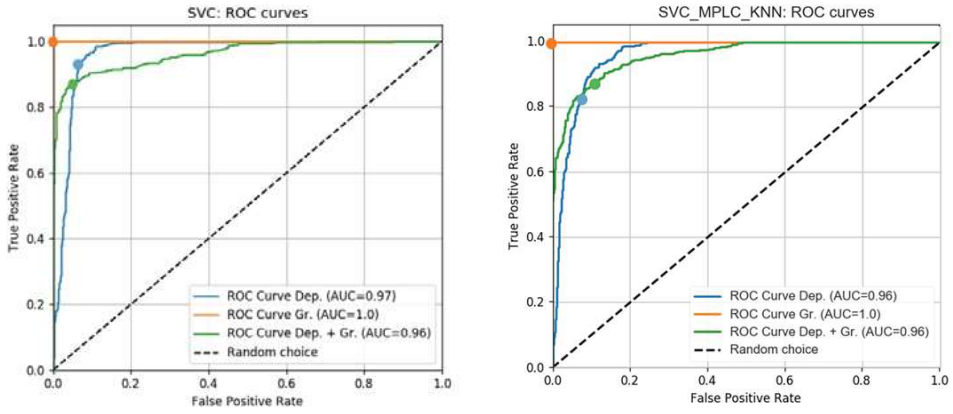
Class 3. Let us now consider KPCA feature extraction. After fitting the extracted features to the classes, we obtain the predictions results shown in Figure 4. These results are pretty congruent with the ones obtained by applying PCA based feature extraction since, also in this case, SVC algorithm performs better than KNN and MLPC. Moreover, we can observe that KNN can outperform MLPC prediction for what concern the class 1 (i.e., deposit only). Conversely, MLPC is able to provide very accurate results for what concern the class 3 prediction (i.e., deposit and groove together). Consistently with these remarks, we have built a major voting classifier based on KNN, MLPC and SVC classifiers, for which the obtained results are provided in Figure 4*d*). In order to provide a deeper insight on the classification results, in Figure 5 we provided the major voting classifier and SVC Receive Operating Curves (ROC) for the three classes considered. Such curves are used to visualize the compromise between performance (true positives) and false alarms (false positives) with respect to the decision threshold used to affect a signal to a particular class, see [12] for more details.

Observing Figure 5*a*), we notice that for all the three classes the SVC ROC curves have a steepest slope compared to the major voting counterparts Figure 5*b*). This turns into, as shown in both plots legends, a higher values of the Area Under the Curve (AUC), which can be considered as an index of classification accuracy. In Figure 6, we have shown the results obtained to assess the robustness of the SVC with respect to Additive White Gaussian Noise (AWGN) corruption applied to the test set samples. We can notice that accuracy in classifications decreases when SNR decreases –which is expected, of course– and that these results slightly less accurate compared to the ones shown in Figure 5*a*) which were obtained with a $SNR = 20$ dB.

CONCLUSIONS

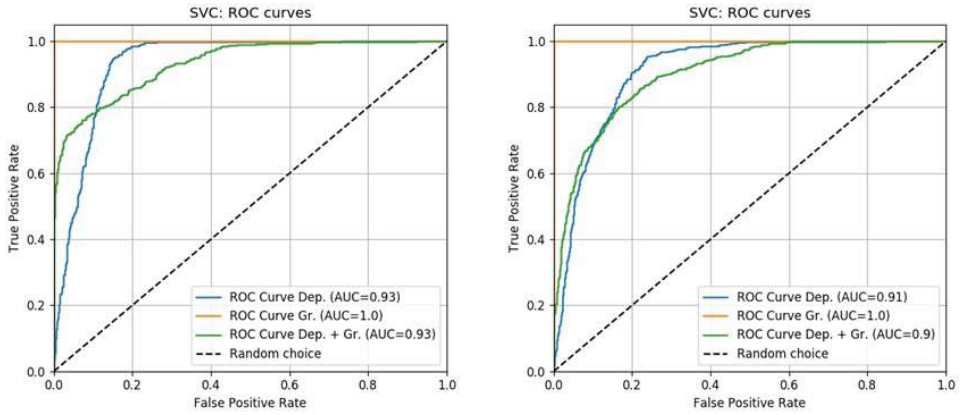
A general methodology of classification has been applied in this paper to ECT signal typically analyzed in the particular industrial application of steam generator tubes inspections. Such tools could quickly carry out a preliminary automatic analysis of large datasets in order to extract a subset of critical indications to be manually analyzed and thus prove useful to human experts currently in charge of the analysis.

Different classifiers were trained and compared in terms of performance, based on a synthetic training set generated with the CIVA software. Results obtained on these synthetic data are quite encouraging and robust to some addition of white noise. An interesting perspective of this work would be, naturally, to evaluate these tools on experi-



SVC **Major Voting**

FIGURE 5. ROC obtained for the three considered classes due to SVC and to major voting algorithms.



SNR = 10 dB **SNR = 5 dB**

FIGURE 6. ROC obtained for the three considered classes are plotted when an AWGN with SNR = 10 dB and SNR = 5 dB is applied on test set samples.

mental datasets. This would raise some other issues like for instance the disproportions of samples in the classes (all indications do not occur with the same frequency in real-life applications), the local corruption of the data or some shift in the acquisition.

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