Ultrasonic flaw signal Classification based on Curvelet transform and Support Vector Machine

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Abstract: ***This paper presents the classification of ultrasonic flaw signal with the use of curvelet transform method and support vector machine. The curvelet transform as a not merely to achieve time frequency manifestation of signal, but also to be used for curvelet signal decomposition and successive parameter assessment. Faults are detected by using a digital flaw detecting method which is considered as the primary tool to obtain the carbon fiber signals as an unbreakable polymer sample with de-lamination and de-bonding. Discrete curvelet transform can be computed ultrasonic signals in time domain by enlightening features are extracted from signals of curvelet coefficients. Finally, SVM chosen by dissimilar techniques are in use as input and train by the classifier. So the kernel function has been checking the data with combination of SVM parameters. Experimental outcome prove the validation and verification of flaw signal with curvelet transform and SVM tool, it deals with classification for ultrasonic signals utmost accurately.***

Keywords: Curvelet transform, SVM, Ultrasonic flaw signals, Kernel function

I. INTRODUCTION

Ultrasonic techniques are working on non-destructive testing methods and procedures for accurate and detection of flaws analysis in ultrasonic signal. These testing techniques are functioning in different procedures based on signal flaw strength. Sometimes these methods bring costly, long and unpredictable analysis for discovery classification and analysis of flaw signal. The progress in earlier period of epochs has enabled the ultrasonic methods and non-destructive techniques authenticate testing. Specific tools employed in Artificial intelligence can also be united along with the automatic signalling events in modern signal processing methods, this type of scenario applied for the identification of various flaw in different engineering resources [1]. The procedure of classification often comprises of three predominant contributions, they are pre-processing of the unique signals, adopting various signal processing methods and pattern classification for feature extraction. Among these methods the most significant method characteristic extraction process, which straightforwardly deprives the correctness and thereby the consistency of flaw classification. The probable dissimilar signal processing analysis methods has been investigated by many researchers in ultrasonic testing [3].

We offered a novel method for ultra flaw signal.

II. METHODOLOGY

Curvelet transform to obtain time frequency representation of signal, but also to be utilized for curvelet signal breakdown and successive parameter assessment. Before this decomposition filters are using for remove noise from data using pre processing. We can use curvelet transform for feature construction and SVM for classify the processed data based on certain conditions. It is a process for finding best signals from flaws. The following procedures are helping for handle the flaw ultrasonic signals [2].

2.1 Data pre-processing

The Pre-processing method of ultrasonic signals consists of amplitude normalization process followed by filtering. For filtering the ultrasonic signal, a method based on discrete curvelet transformation has been employed. This technique is extremely efficient within the specified domain for time period. Furthermore, the ultrasonic signals are scanned to measure the development of signal and noise ratio. The curvelet transformation is a multifaceted resolution analysis technique which is used to predict the period of time frequency rate of the ultrasonic signal. The procedure used for filtering is completely based on the break of signal obtained using curvelet transforms at 'n' no. of levels with group pass filtering along with annihilation to attain the estimate stage and derive the detail coefficients. Then the threshold coefficients and rebuilding of signal from fact and rough calculation coefficients using inverse transformation function [4].

2.2 Curvelet Transform

Discrete Curvelet transform has good signal properties, it is applicable for many real signals and it is also computationally efficient. It is used for different types of processes together with numerical integration, noise diminution, image compression and pattern recognition [5]. The discrete Curvelet transform is a symbol of digital signal processing with respect to time using different filtering methods. Different cutoff frequencies as several scales are used to process the signal. Filters carry out the functions in processing the signal. Scaling the filters in iterations generates wavelets. Scales are identified using the up and down sample technique. The use of filter provides the data in the signal. Therefore, it uses the high and low pass filters over a digitized input signal [7]. The discrete Curvelet transformation is helpful in signifying the image with various passion values which is given by the polynomial function $f(x_1, x_2)$, where $x_1 = 0, 1, 2, 3..., N_1 - 1$ and $y_2 = 0, 1, 2, 3,..., N_2 - 1$, whose discrete Fourier transform is given by

$$\overline{f}(n_{1,}n_2), \sum_{x_2=0}^{N_2-1}\sum_{x_1=0}^{N_1-1} f(x_1,x_2)e^{-2\pi i(\frac{N_1x_1}{N_1}+\frac{N_2x_2}{N_2})} \quad (1)$$

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The discrete Curvelet transformation is a disintegrated value minimalized into the Curvelet coefficients such that

$$f(n_1,n_2)= \sum_{j=1}^{j}\sum_{l=0}^{L_j-1}\sum_{k1=0}^{K_{jl,1}-1}\sum_{k2=0}^{K_{jl,2}-1} D_{jlk}T_{jlk}(x_1,x_2) \qquad (2)$$

Where k= (k1, k2), D is the specified Curvelet on phase vector j denoted by its corresponding direction l and the spatial shift of k.

$$\sum_{jlk} \left|D_{jlk}\right|^2 = \sum_{y1,y2} + |f(x_1,x_2)|^2 \qquad (3)$$

The discrete Curvelet transform function gives a combination of image f through J complete levels, with an orientation of L_j on every level, and a of spatial shifts $K_{jl,1} \times K_{jl,2}$ for every level, where k = (k_1, k_2) and s is the Curvelet function on level j with an orientation l and a spatial shift k. In addition, the Curvelet transform also preserves l^2-norms, which can be denoted by,

$$\sum_{jlk} \left|D_{jlk}\right|^2 = \sum_{y1,y2} + |f(x_1,x_2)|^2 \qquad (4)$$

The above mentioned discrete curvelet transformation function can't join together the image of 'f' into J complete levels, with the orientation of L_j on every level, and spatial shifts of $K_{jl,1}\times K_{jl,2}$ for each direction. The Curvelet is described through its discrete Fourier transformation as

$$\bar{s}_{jok}(n_1,n_2) = V_j(n_1,n_2)\, e^{-2\pi i}(k_1 n_1 / K_{j0,1} + k_2 n_2 / K_{j0,2}) \text{ and } \bar{s}_{jlk} = T^T \theta_1 \bar{T}_{jok} \qquad (5)$$

Here, T_θ is known as shearing matrix, when the grid is subjected to shear on which the Curvelet is evaluated at an angle of $Ø_l$. The slope gradients are designated by the angles $\emptyset_l$ and are equi-spaced. Here v_j is the frequency window function with a compact support function[8].

2.3 Feature Extraction and Selection of SVM

SVM Technique is a set of controlled learning algorithms. 'Pattern recognition problems' can be resolved by using the SVM Technique. Also forecasting the problems, constructing intelligent machines for solving problems, regression approximation techniques and the problems of dependency estimation are some of the areas where SVM application areas. Therefore this architecture determines the generalization abilities of any system at any instance. Support vector machine is used for classifying the different data points of the linear separable data sets that is provided to the system. Hence, SVM can be applicable to both linear and nonlinear circumstances. By using SVM, the separating margin between two classes of variables is tried to be made maximum.

$$h_i(x) = V_i^T . X + v_{i0} = 0 \quad (6)$$

Where $h_i(x)$ = Output feature vector

$V_i^T = \{v_1, v_2, \ldots\ldots, v_n\}$ S = weighing vector

m = number of attributes considered

v_{i0} = a scalar called threshold value or bias value

x = Input feature vector

If x_1 and x_2 are the two values of attributes B_1 and B_2 on the decision hyper plane then the following equation is valid.

$$h_i(x_1) = V_1^T x_1 + v_{i0} = 0 \quad (7)$$

$$h_j(x2) = V_2^T x_2 + v_{i0} = 0 \quad (8)$$

Subtracting the above two equations we Yield the following result:

$$h_i(x_1) = h_j(x_2) = 0 \Rightarrow V_1^T x_1 + v_{i0} = V_2^T x_2 + v_{i0} = 0$$

$$h_i(x_1) - h_j(x_2) = 0 \Rightarrow V_1^T x_1 + v_{i0} - V_2^T x_2 - v_{i0} = 0$$

$$h_{ij}(x_1,x_2) = 0 \Rightarrow V_1^T x_1 - V_2^T x_2 = 0$$

$$\text{i.e. } h_{ij}(x_1,x_2) = 0 \Rightarrow v^T(x_1 - x_2) = 0 \qquad (9)$$

Where (x_1 - x_2) is a vector that is aligned parallel to the decision boundary and is directed from x_1 towards x_2. Since the dot product is zero, the direction for WT must be perpendicular to decision boundary.

Thus, the above separating hyper plane satisfies the prescribed conditions i.e. for any square Xs that is located above the decision boundary and which can be shown as

$$v_1x_1+v_2x_2 + v_{i0} = k > 0 \quad (10)$$

Similarly, any point prescribed in the circle located below the decision boundary, that lies below the separating hyper plane satisfying the context, we can show that

$$v_1x_1+v_2x_2 + v_{i0} = k' < 0 \quad (11)$$

If we label the squares as class +1 and all the circles as class -1, then we can predict the class label X for any test example z in the following way:

$$X_i = \begin{cases} 1, \text{ if } v.\,z + c > 0; \\ -1, \text{ if } v.\,z + c < 0; \end{cases}$$

The hyper planes give the sides of the margin when the weights can be changed and it can be written as

$$H_1: v_1x_1+v_2x_2 + v_{i0} \geq 1, \text{ for } X_i = +1, \qquad (12)$$

$$H_2: v_1x_1+w_2y_2 + v_{i0} \leq -1, \text{ for } X_i = -1, \qquad (13)$$

Connecting the two inequalities of Equations and we get

$$X_i(v_1x_1+v_2x_2 + v_{i0}) \geq 1, \text{ for all i.} \quad (14)$$

The margin can be computed by subtracting the second equation from the first equation. This is equivalent with

1. Having a margin of $\frac{1}{\|v\|} + \frac{1}{\|v\|} = \frac{2}{\|v\|}$
2. Requiring that $v_i^T x + v_{io} \geq 1, \forall x \in v_1$

$$v_i^T x + v_{io} \leq -1, \forall x \in v_2$$

Computing the parameters denoted by w, w_{io} of the hyper plane so that to:

$$\text{Minimize I (v, vio)} = \frac{1}{2}\|V\|2 \qquad (15)$$

$$Xi\,(v_i^T x_i + v_{io}) \geq 1, j=1, 2\ M. \qquad (16)$$

Obviously, minimizing normal gradually increases the margin to a maximum value. This is denoted as a nonlinear quadratic optimization duty topic to a set of linear inequality constraints. The above mentioned crisis can be resolved by reducing Lagrange's function. The conditions proposed by Karush-Kuhn-Tucker (KKT) which minimizes the above equations and also satisfies it are

$\frac{\partial}{\partial w}L(v, v_{io}, ƛ)=0$ and $\frac{\partial}{\partial wo} L(v, v_{io}, ƛ)=0$ where $ƛ_i \geq 0$ i=1, 2…………..N

$$ƛ_i[X_i(v_i^T x_i+v_{io})–1]=0 \quad i=1,2\ldots\ldots\ldots\ldots N$$

Where ƛ denotes the vector of the Lagrange's multiplier $ƛ_i$ and L(v, v_{io}, ƛ) is the Lagrangian function which defined as

$$L(v, v_{io}, ƛ)= \frac{1}{2} v^T v + \sum_{i=1}^{N} ƛ_i[X_i(vi^T x_i+ v_{io})– 1] \qquad (17)$$

Combining the equations (17), (18) and (19), we get

$$V = \sum_{i=1}^{M} ƛ_i X_i x_i \text{ and } \sum_{i=1}^{N} ƛ_i Xi = 0$$

A novel technique has been implemented with the support of SVM for the classification of PQ disturbances.

It has been observed that the SVM technique precisely classifies the PQ disturbances as per the requirement. The proposed methodology using the SVM technique generates a classification rate of about 98.8% which is much better than the technique used for the classification of PQ disturbances.

2.4 Non-linear classifier:

If any two classes specified are in nonlinear case, Eqn. (16) and Eqn. (17) become invalid or void and have different forms. The three categories of the training feature vectors depend on the procedure cited below.

1. Vectors that fall outside the prescribed circle and are classified precisely acquiesce with the constraints

$$Xi\ (v_i^T x_i + v_{io}) \geq 1,\ i=1, 2\ldots\ldots\ldots..M$$

2. Vectors falling inside the prescribed circle and are precisely classified. In hyper plane, these points will be positioned in squares of the variable and they satisfy the inequality

$$0 \leq X_i(v_i^T x_i + v_{io}) < 1$$

3. Vectors that are not classified in any order but are enclosed by circles and obey the inequality

$$Xi\ (v_i^T x_i + v_{io}) < 0$$

All these three cases can be categorized as single type of elements by introducing a novel objective function Ø which is given by

$$Xi\ (v_i^T x_i + v_{io}) \geq 1 - Ø_i$$

For category X-1: $Ø_i = 0$ for categorX-2: $0 \leq Ø_i < 1$ for category X-3: $Ø_i \geq 1$

The variable $Ø_i$ is called as slack variables. The Goal is to make the margin as huge as possible at the equivalent time specified to maintain the number of points with Ø > 0 as small as possible. This equivalent to assigning a minimal cost function denoted by

$$I\ (v, v_{io}, Ø) = \frac{1}{2} v^T v + D \sum_{i=1}^{M} J(Øi)$$

Where Ø is the vector of the parameters Øi and

$$X_i = \begin{cases} 1, \text{ if } v.\ z + c > 0; \\ -1, \text{ if } v.\ z + c < 0; \end{cases}$$

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$$ƛ_i[X_i(v_i^T x_i + v_{io}) - 1] = 0 \quad i=1,2\ldots\ldots\ldots\ldots..N$$

Where ƛ denotes the vector of the Lagrange's multiplier $ƛ_i$ and L(v, v_{io}, ƛ) is the Lagrangian function which defined as

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The variable $Ø_i$ is called as slack variables. The Goal is to make the margin as huge as possible at the equivalent time specified to maintain the number of points with Ø > 0 as small as possible. This equivalent to assigning a minimal cost function denoted by

$$I\ (v, v_{io}, Ø) = \frac{1}{2} v^T v + D \sum_{i=1}^{M} J(Øi)$$

Where Ø is the vector of the parameters Øi and

$$Ø_i = \begin{cases} 1, \text{ if } Ø_i > 0; \\ 0, \text{ if } Ø_i = 0; \end{cases}$$

The parameter D is a positive constant value that controls the relative influence of the competing terms mentioned in the equation. By minimizing Lagrange's function all the worst issues can be resolved.

$$L\ (v, v_{io}, Ø, ƛ, ú) = \frac{1}{2} \|v\|^2 + D \sum_{i=1}^{M} Øi - \sum_{i=1}^{M} Øiúi - \sum_{i=1}^{M} ƛ_i\ [Xi\ (v_i^T x_i + v_{io}) - 1]$$

The equivalent Karush-Kuhn-Tucker conditions that minimizes the above equations and that has to satisfy the governing conditions are

$$\frac{\partial L}{\partial w} = 0 \text{ or } v = \sum_{i=1}^{M} \lambda_i X_i x_i$$

$$\frac{\partial L}{\partial wo} = 0 \text{ or } \sum_{i=1}^{M} \lambda_i X_i = 0$$

$$\frac{\partial L}{\partial úi} = 0 \text{ or } \sum_{i=1}^{N} D - úi - \lambda_i = 0 \quad J = 1,2\ldots\ldots M$$

$$\lambda_i \left[X_i(v_i^T x_i + v_{io}) - 1 + Ø_i\right] = 0, ú_i Ø_i = 0, ú_i \geq 0, \lambda_i \geq 0 \quad i = 1, 2\ldots\ldots M$$

In nonlinear case, SVM maps the input vectors denoted as y into a high dimensional space through some nonlinear mapping techniques.

2.5 Multi-classifier:

In the recent Years, a discrete methodology named as multi-class SVM, which can classify more than two dataset, are proposed. For each one of these classes, we can apparently design an optimal discriminate function given by $h_i(x)$, i=1, 2…N, so that $h_i(x) > g_j(y)$, ∀j #i, if y ∈w_i. Classification is attained as per the following rule: Assign x in v_i, if i = argument $x_k\{h_k(x)\}$.

In OAO training process, all the classes with machine depending on comparison with each other and each data set is trained by assuming that all the data set belongs to a respite data set. For a problem under k-class, while OAO methodology constructs k*(k-1)/2 hyper planes, OAA methodology constructs k hyper planes only.

Algorithm used for classification of the extracted features using KKT-conditions:

1. Input: $\{(\bar{y}, x_1)\ldots(\bar{y}_n, x_n)\}$.
2. Initialize for i = 1, . . . , n:
3. $\bar{\tau}i = \bar{o}$
4. $E_{i,r} = -\beta\delta_r, y_i (r = 1...k)$
5. $B_i = K(\bar{y}, \bar{y})$
6. Repeat:
7. Calculate for i = 1. . . n: $\varphi_i = \max_r F_{i,r} - \min_{r:\tau i,r<\delta yi,r} Fi,r$
8. Set: O = arg max{ψi}
9. Set for p = 1. . . k : $Dr = \frac{Fp,r}{Ap} - \tau p,r + \delta r, y_p$ and $\theta = \frac{1}{k}\sum_{r=1}^{k} Dr - \frac{1}{k}$
10. Call: $\bar{\tau}^*p$ =Fixed Point Algorithm ($\bar{C}$, θ, ∈/2).
11. Set: $\Delta\bar{\tau}p = \bar{\tau}^*p - \bar{\tau}p$
12. Update for i = 1. . . m and r = 1. . . k:
13. $E\ i.r \leftarrow E\ i.r + \Delta\tau p,r\ K(\bar{y}p, \bar{y}I)$
14. Update: $\bar{\tau}p - \bar{\tau}^*p$
15. Until $\psi_p <$ _β
16. Output : $H(\bar{x}) = \arg\max_r.\{\sum_i \tau_i, rK(\bar{y}, \bar{y}_i)\}$.

SVMs were formerly established to execute binary classification only. The classification of data into more than two classes, called multiclass classification technique, which is frequently and predominantly used in remote sensing applications. The Karush–Kuhn–Tucker conditions for the optimization issue. Although convergence of this algorithm is assured to a certain extent, heuristics are used to choose the suitable pair of multipliers precisely so as to accelerate the rate of convergence. In this methodology, we can create more SVM classifiers for all the possible pairs of classes. The standard formulas for finding the statistical parameters of every signal. We also compute dissimilar values root mean square value and absolute values [10].

(1) Mean value : $AVG = \frac{1}{M}\sum_{i=1}^{M} x_i$

(2) Standard deviation : $STD = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(y_i - AVG)^2}$

III. RESULTS AND DISCUSSIONS

The following table describes the training table, recognition rate of test data and recognition rate of training data with kernel function. The SVMs with RBF kernel functions are best for mean identification rates of linear and polynomial kernels. Due to the exponential processing complications of support vector machine with RBF kernels had utmost training time. Let us attention on the support vector machine include polynomial kernel function (*p*=3) and RBF kernel function (*p*=0.1), it is recognized as Poly3 and RBF 0.1 support vector machine. Support vector machine get 98.5% in Poly3 of training identification rate within 81.4 seconds. In this scenario, two top de-lamination flaws of the CFRP samples were classified as middle de-lamination, these are not affected by positive or negative for every point. In this process of comparison to RBF 0.1 support vector machine, 97.95% of training identification rate within 271.1 seconds, support vector machine receives 228% in Poly3, development for training efficiency. So 1.26% losses for identification rate of flaw signals. Finally Poly3 Support vector machine can completely achieve the trade-off among the processing complexity and classification performances of flaw ultrasonic signals.

Table 1. Training Times of SVMs and Identification Rates with dissimilar Kernel Functions

Kernel function	Identification of training data (%)	Identification of test data (%)	Training time (s)
Linear function (*C*=1)	92.25	88.5	20
Polynomial function, *p*=2 (*C*=0.1)	96	91	68.5
Polynomial function, *p*=3 (*C*=0.1)	96.5	93.5	82.4
RBF Network, K=10 (*C*=1)	96.65	92.25	219.1
RBF Network, K=10 (*C*=1)	98.5	93.5	231.3
RBF Network, K=0.1 (*C*=1)	97.95	93.75	271.1

Table 2. Parameters of Back Propagation Network

Parameters of BP	Value
Number of input features	6
hidden layer of Activation function	Tan sigmoid transfer function
output layer of Activation function a	Tan sigmoid transfer function
Training algorithm	Trainscg
Number of neurons at hidden layer	13
Throughput goal	0.001
Network structure	6-13-6

Table 3. Comparison among Back Propagation Network and SVMs

Classifiers of signal	Identification of training data (%)	Identification of test data(%)	Training time(s)
Back Propagation Network	91.25	86.25	85
Support Vector Machine	98.75	93.75	170.5

The above tables 2 and 3 show the information regarding the standard formulas for discovery the statistical parameters of every signal. We also compute dissimilar values of root mean square and absolute values. Based on these values successfully finding the flaw ultrasonic signals.

IV. CONCLUSION

Ultrasonic flaw signal classification and analysis by using curvelet transforms and support vector machine. The curvelet transform as a not merely to attain time frequency demonstration of signal, but also to be used for curvelet signal decomposition and successive parameter assessment. Faults are detected by a digital flaw detector; it is primary device to get the signals of carbon fiber indestructible polymer sample with de-lamination and de-bonding. The curvelet coefficients from discrete curvelet transform can be processed ultrasonic signals in time domain for feature extraction. Finally, SVM chosen by dissimilar techniques are in use as input and train by the classifier. Checking the signal data with the help of kernel function support vector machine parameters. Statistical results show the verification and validation of signal with the help of curvelet coefficients and support vector machine. This method generates best analysis and classification of ultrasonic signals.

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