Diagnostic of Defects with Inductive Thermography Imaging System using PSO Algorithm

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Abstract— Background/Objectives: This paper proposes an unsupervised method for diagnosing and monitoring defects in inductive coils. The objective of the present paper is to locate the exact crack location and diagnose easily. Methods/statistical analysis: The core of the method is based on the signal processing-based pattern extraction algorithm using Sparse Greedy based Principal Analysis(SGPCA).The proposed method is fully automated and diagnosis of defects is done by Particle Swarm Optimization algorithm(PSO).By implementing PSO algorithm, the cracks on the complex surface will be detected easily. Findings: It is shown that the SGPCA analysis for detecting the defects is not suitable for all type of metals. An internal functionality is built in the proposed algorithm to control the sparsity of SGPCA. Experimental tests with other methods have been conducted to verify efficiency of proposed method. Application/ Improvements: Improvement in efficiency of inductive coils.

Key words: Inductive Thermography Imaging System, PSO Algorithm

I. INTRODUCTION

Imaging diagnostic system for defect detection is highly demanded in industry. This has been applied on inspection of electronic chips or dies in semiconductor production lines. [4]Acciani et al. Extracted the features of the regions of interest in test images and then built multilayer neural networks for defect detection on solder joints in surface mount technology of industry. Proposed defect inspection system of solar modules in electroluminescence (EL) images. A proposed fuzzy spectral and spatial feature integration method for classification of nonferrous materials in hyper spectral data. All these methods recognize that image based defect diagnostic system[8] is a wide group of analysis technique used in science and industry to evaluate the properties of material, component or system without causing damage. Infrared thermography systems have reached a prominent status as a nondestructive testing and evaluation (NDT&E) image diagnostic method with the advantages of being fast, and providing non-contact, non-interaction, real-time measurements over a large detection area with a long range, security of personnel, and relatively easy interpretation of results. Infrared thermography can be used to assess and predict the structure or behavior beneath the surface by measuring the distribution of infrared radiation and converting the measurements into a temperature scale. Inductive thermography (IT) system which combines two techniques: Eddy Current (EC) and thermography has the potential with an increasing span of application Comparing with other thermography NDT&E systems, the heat of IT is not limited to the sample surface, rather it can reach a certain depth, which governed by the skin depth of eddy current. Furthermore, IT focuses the heat on the defect due to friction or eddy current distortion, which increases the temperature contrast between the defective region and defect-free areas. Ambiguous case prevents the use of IT system in automated environments.

II. EXISTING SYSTEM

Eddy current pulsed thermography (ECPT) is a kind of methods which is the most widely used such as penetration depths measurement in metallic materials, small defects detection for compressor blades, probability of detection (POD) estimation of fatigue cracks, impact evaluation in carbon fiber reinforced plastic (CFRP), corrosion and blister detection under coating and multiple cracks detection. [1]All these works require signal processing tools to do defects analysis. In ECPT, several thermal transient response features have been used as an indicator of defect status, which is critical for acceptance/rejection decisions for maintenance and lifetime prediction. Most methods are limited on manually selecting the proper contrast components. To enhance the flaw contrast and improve noise rejection qualities, pattern based image enhancement has been conducted by introducing the raw data upon a set of orthogonal basis functions. Fourier transform was applied to pulsed thermography, and enhanced the flaw-contrast significantly using phase map. Influence of non-uniform heating and surface emissivity variation was removed by using a Fourier transformation based image reconstruction algorithm. Instead of a prescribed set of basic functions, empirical orthogonal functions were also employed to maximize the anomalous patterns of transient response. The efficiency of Principal Component Analysis (PCA) was compared on thermography features extraction by considering the initial sequence as either a set of images or a set of temporal profiles.

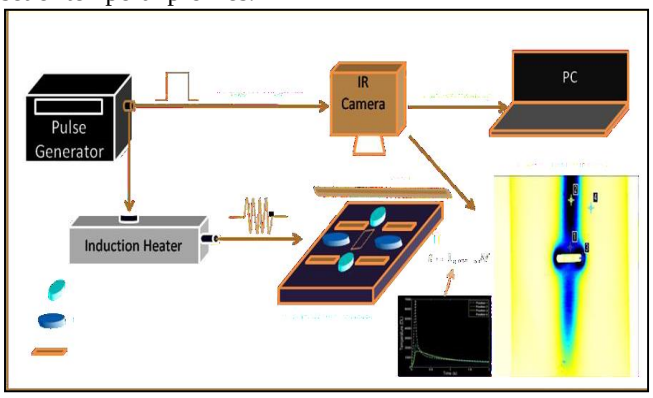

Fig. 2.1: Block Diagram of Existing System

In addition, the Independent Component Analysis (ICA) and Non-negative Matrix Factorization (NMF) are proposed for defect characterization in IT system. However, most pattern extraction based methods are only employed as a signal processing tool. [2]The physics mechanism is not fully linked to provide the benefits on defect detection and

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while the results are acceptable, they are not completely accurate. This ambiguous case prevents the use of IT system in automated environments.

A. SGPCA Analysis

The sparse modeling of signals which has proven to be effective in signal processing, denoising, deconvolution, compressive sensing reconstruction, inpainting, data mining, multimedia, nonnegative matrix factorization and etc. Most natural signals exhibit such sparsity property in adequately chosen signal representations. These include the wavelets, the curvelets or even adaptively learned signal representations. Greedy algorithms have been widely used to find approximate solutions quickly to combinatorial optimization problems. In a few cases, optimal solutions are guaranteed. Greedy algorithms for sparse approximation have inspired less adaptive methods. Matching pursuit (MP) can be converted to a low complexity adaptive form, as done in, and been extended to orthogonal MP (OMP) as well as stage-wise OMP [3]; Compared with convex relaxation algorithms, greedy pursuits need more measurements, but they tend to be more computationally efficient. Sparsity has been exploited in recent unsupervised pattern recognition methods. The group of research interest focuses on the low-rank and sparse components via convex optimization have also been attractive, the robust PCA, is proposed iterative thresholding methods with low complexity, but with low speed of convergence. Lin et al. Proposed accelerated proximal gradient (APG) methods which are faster and more accurate than robust PCA. The latest approach such as variational Bayesian and Markov chain Monte Carlo (MCMC) based sparse PCA with specific prior where the model parameters and hyper parameters are adapted by using the . In all cases, a fully Bayesian treatment is applied to inference. While these approaches increase the accuracy of specific application and works efficient when suitable prior is selected.

Moreover, it consumes significantly high computational complexity at each iteration to adapt the parameters and its hyper parameters. The contributions of the current work lie in the development of the physics mechanism that underlies the IT system and a derivation of a mathematical model that bridges the gap between the physics mechanism and signal processing analysis. The aim is to develop a data-analytics algorithm to extract anomalous patterns in the IT system. A physics-based signal processing approach combining sparse greedy Principal Component Analysis (SGPCA) is developed to identify and search the defect region in the sample.

The model represents a low-rank variable as a sparse bilateral factorization with greedy-based optimization to reduce the computational complexity during the sparse pattern extraction stage. The physics mechanism as to why sparse information benefits the IT heating phase[9] will also be discussed in details. The comparison in terms of the probability of detection and computational complexity has been undertaken for different sparse pattern. Future work will focus on samples with complex surface condition, e.g. roughness and emissivity variation. Complexity defects detection, e.g. subsurface defect in metallic material, impact damage and delamination in carbon fiber structures will also be investigated.

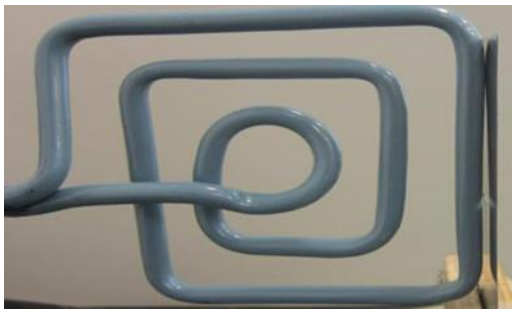

Fig. 2.2: Inductive Coil

III. PROPOSED METHODOLOGY

To detect cracks on metal surfaces using Particle Swarm Optimization algorithm. In proposed method we also concentrate on physical characteristic changes and Complexity defects. We use Particle swarm Optimization technique to detect the cracks and minor defects.

A. Block Diagram of Proposed Method

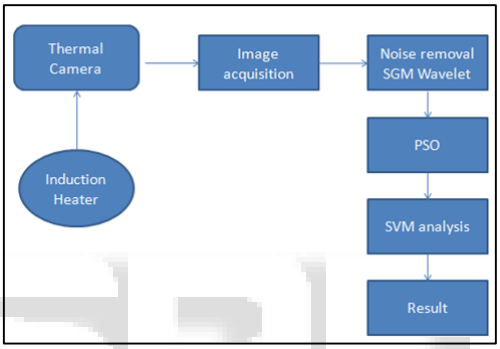

Fig. 1: Block Diagram of Proposed Method

1) PSO Algorithm

Particle swarm optimization (PSO) is a technique used to explore the search space of a given problem to find the settings or parameters required to maximize a particular objective. [5]Optimization is the algorithm by which one finds the maximum or minimum value of a function or process. This mechanism is used in fields such as physics, chemistry, economics, and engineering where the goal is to maximize efficiency, production, or some other measure. The PSO algorithm works by simultaneously maintaining several candidate solutions in the search space. During each iteration of the algorithm, each candidate solution is evaluated by the objective function being optimized, determining the fitness of that solution. Each candidate solution can be thought of as a particle "Flying" through the fitness landscape finding the maximum or minimum of the objective function.

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

Formally, let f: $\mathbb{R}^n \rightarrow \mathbb{R}$ be the cost function which must be minimized. [6]The function takes a candidate

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solution as argument in the form of a vector of real numbers and produces a real number as output which indicates the objective function value of the given candidate solution. The gradient of *f* is not known. The goal is to find a solution a for which $f(a) \leq f(b)$ for all b in the search-space, which would mean a is the global minimum. Maximization can be performed by considering the function $h = -f$ instead.

Let *S* be the number of particles in the swarm, each having a position $x_i \in \mathbb{R}^n$ in the search-space and a velocity $v_i \in \mathbb{R}^n$. Let p_i be the best known position of particle *i* and let g be the best known position of the entire swarm. A basic PSO algorithm is then:[10]

a) For each particle i = 1, ..., S do:

- Initialize the particle's position with a uniformly distributed random vector: $x_i \sim U(b_{lo}, b_{up})$, where b_{lo} and b_{up} are the lower and upper boundaries of the search-space.
- Initialize the particle's best known position to its initial position: $p_i \leftarrow x_i$
- If ($f(p_i) < f(g)$) update the swarm's best known position: $g \leftarrow p_i$
- Initialize the particle's velocity: $v_i \sim U(-|b_{up}-b_{lo}|, |b_{up}-b_{lo}|)$

b) Until a termination criterion is met (e.g. number of iterations performed, or a solution with adequate objective function value is found), repeat:

- For each particle i = 1, ..., S do: For each dimension d = 1, ..., n do:
- Pick random numbers: $r_p, r_g \sim U(0, 1)$
- Update the particle's velocity: $v_{i,d} \leftarrow \omega\, v_{i,d} + \varphi_p\, r_p\, (p_{i,d}-x_{i,d}) + \varphi_g\, r_g\, (g_d-x_{i,d})$
- Update the particle's position: $x_i \leftarrow x_i + v_i$
- If ($f(x_i) < f(p_i)$) do:
- Update the particle's best known position: $p_i \leftarrow x_i$
- If ($f(p_i) < f(g)$) update the swarm's best known position: $g \leftarrow p_i$

c) Now g holds the best found solution.

The parameters ω, φ_p, and φ_g are selected by the practitioner and control the behaviour and efficacy of the PSO method[7].

The PSO algorithm consists of just three steps, which are repeated until some stopping condition is met :

- Evaluate the fitness of each particle
- Update individual and global best fitness and positions
- Update velocity and position of each particle

The first two steps are fairly trivial. Fitness evaluation is conducted by supplying the candidate solution to the objective function. Individual and global best fitness and positions are updated by comparing the newly evaluated fitness against the previous individual and global best fitness, and replacing the best fitness and positions as necessary. The velocity and position update step is responsible for the optimization ability of the PSO algorithm[10].

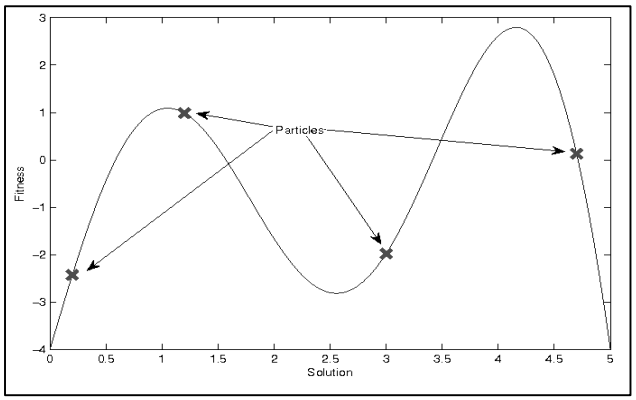

Fig. 3.2: Initial PSO State

d) Original velocity update equation

$$\mathbf{v}_i(k+1) = \text{Inertia} + \text{cognitive} + \text{social}$$

$$\mathbf{v}_i(k+1) = \omega \times \mathbf{v}_i(k) + c_1 \times random_1() \times (PBest_i - \mathbf{x}_i(k)) + c_2 \times random_2() \times (GBest - \mathbf{x}_i(k))$$

- w,c_1,c_2: Constant
- $random_1()$, $random_2()$: random variable

e) Position update

$$\mathbf{x}_i(k+1) = \mathbf{x}_i(k) + \mathbf{v}_i(k+1)$$

2) PSO Flow Chart

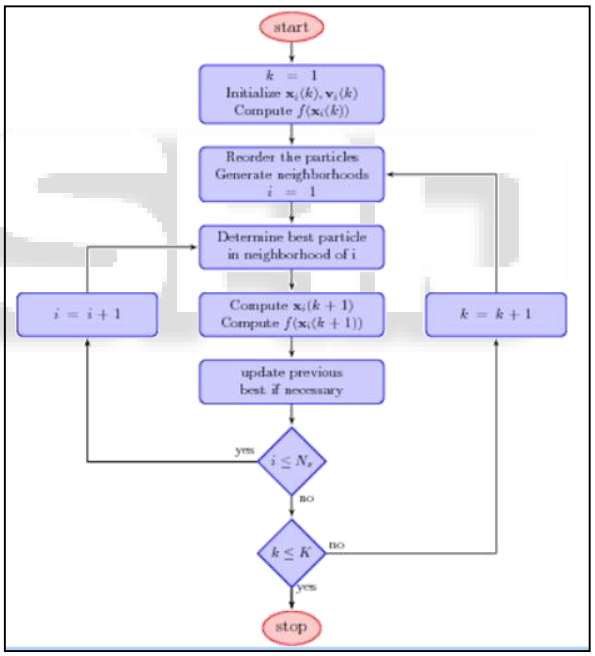

Fig. 3: PSO Flow Chart

B. SVM Analysis

Support vector machines [11] are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

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In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are not labelled, a supervised learning is not possible, and an unsupervised learning is required, that would find natural clustering of the data to groups, and map new data to these formed groups. The clustering algorithm which provides an improvement to the support vector machines is called support vector clustering and is often used in industrial applications either when data is not labelled or when only some data is labelled as a preprocessing for a classification pass.

C. Simulation Results

1) SGM Wavelet

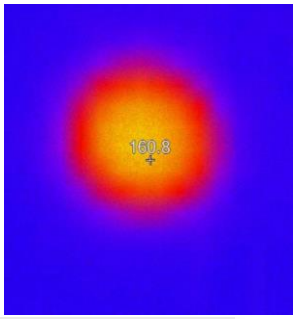

Fig. 4.1: With Noise

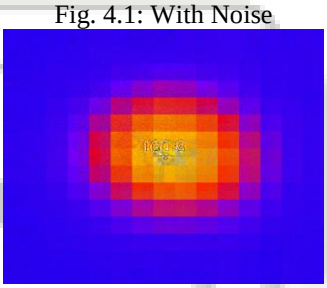

Fig. 4.2: Without Noise

2) PSO Algorithm

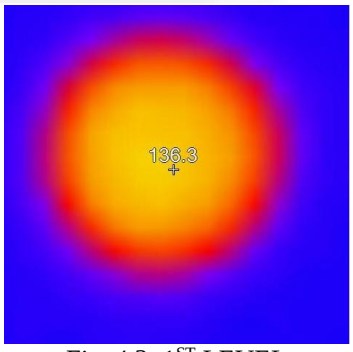

Fig. 4.3: 1ST LEVEL

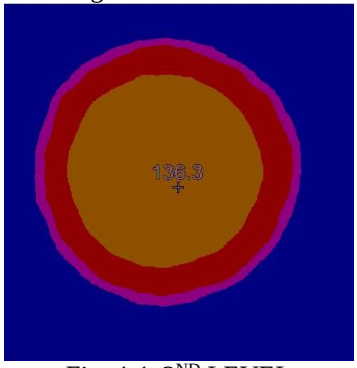

Fig. 4.4: 2ND LEVEL

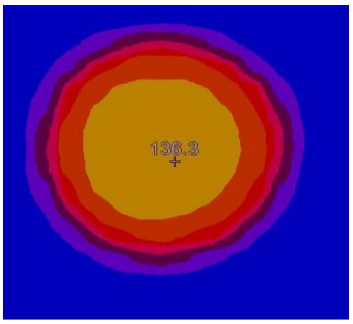

Fig. 4.5: 3RD LEVEL

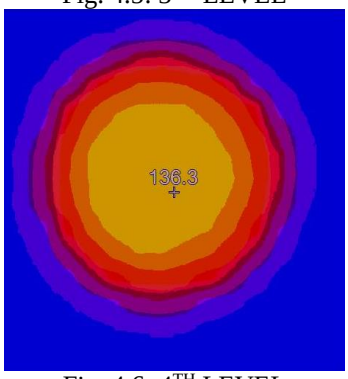

Fig. 4.6: 4TH LEVEL

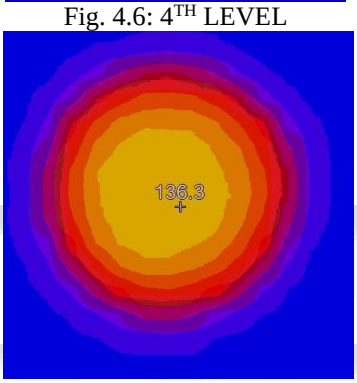

Fig. 4.7: 5TH LEVEL

3) SVM Analysis

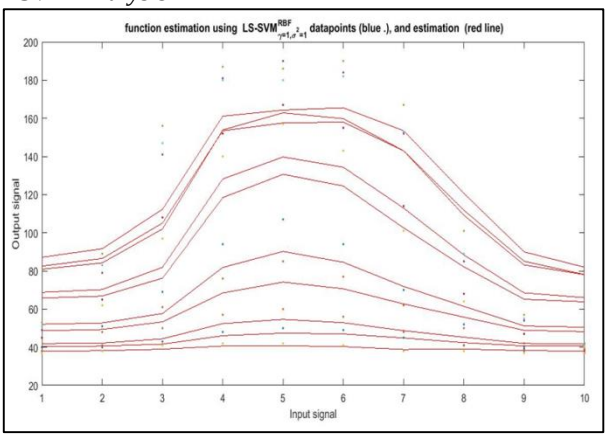

Fig. 4: Graph SVM Analysis

IV. CONCLUSION AND FUTURE WORK

The proposed method has been tested on both man-made and natural defects from industry. Future work will focus on samples with complex surface condition, e.g. roughness and emissivity variation. Complexity defects detection, e.g. subsurface defect in metallic material, impact damage and delamination in carbon fiber structures will also be investigated.

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