

Self Organizing Analysis Platform for Wear Particle

Qurban A. Memon, and Mohammad S. Laghari

Abstract—Integration of system process information obtained through an image processing system with an evolving knowledge database to improve the accuracy and predictability of wear particle analysis is the main focus of the paper. The objective is to automate intelligently the analysis process of wear particle using classification via self organizing maps. This is achieved using relationship measurements among corresponding attributes of various measurements for wear particle. Finally, visualization technique is proposed that helps the viewer in understanding and utilizing these relationships that enable accurate diagnostics.

Keywords—Neural Network, Relationship Measurement, Self organizing Clusters, Wear Particle Analysis.

I. INTRODUCTION

MICROSCOPIC applications have been one of the important areas in the field of automation for on-line/off-line visual inspection systems in industry and for long term availability of inventory in ware houses. These systems include analysis of microscopic wear particles. Any change in the steady state operation of the machine creates a change in the normal wear mechanism. This change once transported by a lubricant from wear sites carries important information relating to the condition of engines and other machinery. Researchers have used this information to diagnose wear producing modes and thus attempt to predict wear failures in machines [1], [2].

For the purpose of objective diagnosis, the identification and analysis of these particles have been reported in literature using various automation techniques. The interested reader is referred to [3]-[5]. The aim of the overall research has been to develop an image analysis and in some cases knowledge based system to classify wear particles for the objective under study. In [6], the authors have discussed an intelligent expert system via Internet using combination of an expert system and a neural network. The respective authors have only discussed classifications where desired ones are known and corresponding mapping is done through a neural network. Thus they have not fully utilized the potential of the neural networks for relationships and associations, and for such objective mere database distributions are utilized.

The term Wear Particle is associated with the field of "Tribology". Tribology is the study of wear, friction and lubrication. Different sizes of filters, Ferrography and Magnetic Chip Detectors (MCD) are such techniques [2], [3], [7]. The essential requirement in terms of wear is to determine its extent

and rate of change in relation to the type of wear and its source.

Classification: Wear manifests itself in numerous ways and is likewise categorized according to difference concepts of its mode, underlying mechanisms and its wear severity or rate [8]. Generally, two types of analysis are carried out to identify particles; one relates to profile attributes – size, outline shape and edge detail, the other covers surface texture classification. Particle features could be divided in terms of their size, quantity, morphology and composition. Such particles features are classified in terms of their morphological attributes. Experts characterize the particles with particular morphology and relate these to known wear modes. The analysis yields specific information about the condition of moving surfaces of the machine elements from which they are produced, the mechanism of their formation, and mode of wear in operation in the system from which they are extracted [5], [10]. The classification used for most of the objective analysis includes six morphological attributes of particles: size, shape, edge detail, thickness ratio, color, and surface texture [4], [5], [9].

Relationship Network: Relationship network analysis concerns itself with the measuring of relationships and flows between different measurements of attributes [10]. We may be able to model such an analysis as a relationship network, as each individual measurement of the particle is an entity and their interactions imply relationships and flows. Such relationship networks can provide a mathematical analysis of the relationships in an expert system, yet visual representations are often easier to comprehend. The network is modeled as a graph, consisting of a set of nodes and edges, where each node represents a measurement and an edge represents a relationship between a pair of nodes, as shown in Fig. 1. The Fig. 1 represents O_1 , O_2 , and O_3 as wear particle measurements of the same machine but taken at a different time, where as M_1 , M_2 , M_3 ; P_1 , P_2 , P_3 and N_1 as measurements of similar particle(s) but taken from an experiment on a similar machine in a different geographic location, assuming that such measurements are somehow forming a database. The connection between any two measurements is weighted, and we call this weighted link as an edge of the relationship. Thus this edge can be strong and/or weak depending on the value of the corresponding weight. This relationship diagram can be exploited for forming similar clusters having similar and close wear modes. The question remains how such a relation is to be inferred and how many of such experiments are needed for ensuring confidence that a stronger relationship has occurred to lead to better judgment.

Inferring Relationship Strengths and Visualization: The cluster analysis can be used to monitor the database (built from such particle measurements) and infer the relationship network structure for us. Each measurement (of attributes of a machine particle) carries a unique space in the database. Thus the task is

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to develop a close coupling between a database management system (DBMS) and a system providing intelligent wear particle analysis facilities. To begin with, the inferred relationship graph contains only a set of nodes to represent the measurements in the expert system. All that remains are, to build the set of weights (can be called as distances) to be assigned to edges. Visualization of a relationship networks is also important, as it allows the user to determine facts about nodes and relationships between nodes more rapidly than examining the raw mathematical model. For example, the prominence of a node in the relationship network can be determined by its centrality and/or color. The authors in [1]-[9] have not addressed a self organizing relationship structure with an evolving feature in their approach for deriving better judgment in case of wear particle analysis. In our work, we have addressed wear particle analysis from this perspective.

II. DATA ACQUISITION AND MODELING

The hardware tool used is the Leica Quantimet *Q500MC*, an easy-to-use image processing and analysis system [11]. The color image analyzer uses a CCD camera, and controlled by software called *QWIN* to sample the image. It is an image analysis toolkit running under the industry standard Microsoft Windows environment. The system provides several classes of measurements ranging from semi-manual planimetry to semi-automatic particle sizing [11]. The essential measurement procedures are: size distribution, area, positional coordinates, Ferret diameter measurements, length, width, perimeter, aspect ratio, roundness-factor, texture image, color, thickness and the count of the particles. Procedures are developed to provide a set of data to investigate particle profile and texture analysis, which are based on the four morphological attributes of size, shape, edge detail and texture. For morphological data procedures, interested reader is referred to [12]-[15]. The six parameters (i.e., size, shape, edge detail, thickness ratio, color, and surface texture) were recorded and form the crux of wear particle analysis. The described six morphological attributes are classified by their options or features. For example, edges of a wear particle can be smooth, rough, straight, serrated, or curved. Particle attribute priority gives each particle type a level of priority. This is essential for identification where in some situations the individual features of the six attributes alone are not sufficient to distinguish between some particle types, since many particle types have some attribute features in common. These six parameters capture a fairly large and extremely essential amount of information and hence we intend to use these parameters for modeling. It should be emphasized here that since analysis result is not known and that a number of relevant measurements and corresponding weights are needed to finally help enable better judgment on this analysis, it would be wise to explore such model, which helps in chaining events and finally leading to the judgment. In fact, the model should infer itself abstractions to form group or cluster related patterns/incidents.

As neural networks have been reported [16] to be flexible (can learn), fault tolerant (can cope with fuzzy/inconsistent data), robust (fault tolerant), and can solve difficult problems,

hence its learning/training features in absence of a supervisory role can be used to model the scenario.

The Self-Organizing Map (SOM) with its related extensions has been the most popular artificial neural algorithm for use in unsupervised learning and data visualization. More than 5,000 publications have been reported in the open literature, and many commercial projects employ the SOM as the tool for solving hard real-world problems [17], [18]. Self-organizing networks could be both supervised or unsupervised, and have four additional properties:

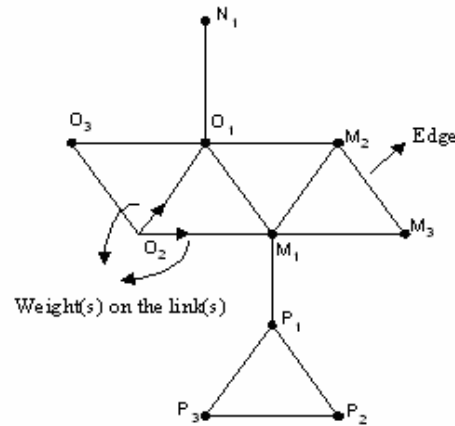


Fig.1 A simple relationship network

- Each weight represents a certain input.
- All neurons receive the input patterns at the same time.
- The neuron with the largest response wins.
- A method of reinforcing the competitive learning.

Unsupervised learning allows the network to find its own energy minima and is therefore more efficient with pattern association. Obviously, the disadvantage is that it is then up to the user to interpret the output. There are quite a few types of self-organizing networks, like the Instar-Outstar network, the ART-series, and the Kohonen network [18]. The Kohonen network is probably the best example, because it is quite simple yet introduces the concepts of self-organization and unsupervised training easily. For purposes of simplicity and training, we explore the Kohonen network for classification of wear particle analysis.

The self-organizing feature of Kohonen networks allows the otherwise incomparable values be mapped onto a two-dimensional plane with similar data residing in closer proximity. Based upon the data (of six elements) received from various experiments on wear particle, such a mapping of wear particle parameters can also be generated to train the network. Since neural network accepts numerical values, hence six variables can typically be mapped as shown in Table 1. The values chosen for mapping were arbitrary: like six different sizes, five different shapes, four different edge details, seven different thickness values, four different colors, and six textures of surface.

III. MAPPING OF DATA AND SIMULATIONS

As discussed earlier, neural networks can be used to model such scenario, the next step before us is: How do we construct the network? For problem under study, Kohonen networks are known to solve unsupervised learning problems [17]. Essentially, they do the clustering job – data that are closer together are clustered into the same groups. The architecture of such network can be reduced to following key issues: Input layer, and output layer [17].

The input layer receives those six parameters, and thus the number of input nodes (i.e., six values) equals the dimension of the input vector. The output layer processes the input data and gives an output. It is actually a two-dimensional sheet. The number of output nodes determines the maximum number of classes to be found. Each neuron (node) in the output sheet represents a cluster, or alternatively a set of common features. The proposed system uses Kohonen Self Organizing Maps (SOM) to plot a matrix of the available data. This is a two dimensional plane containing 4096 cells (64 x 64 plot), where the wear particle data is mapped into different cells representing different wear modes of particles. The size of 64x64 wear modes is arbitrary (although adequate for most of the machine part models) and has been selected only for simulation purposes. The SOM takes the data from the database and decides the position of a wear particle case based on the parameters attached to it. These are the same parameters discussed above and are noted for every wear particle measurement. The general model of the proposed scheme is shown in Figure 2, where we have shown wear particle database in addition to its analysis system. It contains 64x64 output nodes along with 6 input nodes, hence total of $(6 \times 64 \times 64 \approx) 24576$ weights of the network are to be initialized and updated each time an input pattern (case) is presented for training. This process continues till convergence of its training algorithm. The algorithm used for training of the network typically undergoes following steps [19]:

- (a) Define input value range
- (b) Present an input pattern (i.e., six data values)
- (c) Compute distance between input and weight, and sum them
- (d) Select the output node with minimum distance – this is the node that is closest to the input vector
- (e) Alter the weights for the closest node (and also its neighbors) so that it is even nearer to the input vector.
- (f) Go to step (b) until convergence is achieved.

Effectively, this training algorithm is very simple, following a familiar equation:

$$\Delta w_{ij} = k(x_i - w_{ij})$$

where k is the learning coefficient, x is input pattern, w_{ij} is weight in two dimensions, and Δw_{ij} is the change in the weight. So all neurons in neighborhood (say N) to neuron x_{40} (i.e., the one with minimum distance) have their weights adjusted. The adjustment of k and N is an area of much research, but Kohonen suggested splitting the training up into two phases. Phase 1 reduces down the learning coefficient from 0.9 to 0.1 (or similar values), and the neighborhood reduces from half the diameter of the network down to the immediately surrounding cells ($N = 1$). Following that, phase 2 reduces the learning

coefficient from perhaps 0.1 to 0.0 but over double or more the number of iterations in phase 1. The neighborhood value is fixed at 1. We see that the two phases allow firstly the network to quickly 'fill out the space' with the second phase fine-tuning the network to a more accurate representation of the space.

TABLE I
DATA MAPPING FOR A PARTICULAR NEURAL NETWORK

Str.No.	Wear Particle Parameters	Choices/values	Labels
1	Size	a_1, a_5	1-6
2	Shape	b_1, b_5	1-5
3	Edge Detail	c_1, c_4	1-4
4	Thickness ratio	d_1, d_7	1-7
5	Color	e_1, e_4	1-4
6	Surface Texture	f_1, f_5	1-6

IV. VISUALIZATION OF DATA

After we have inferred the relationship cluster for wear particle measurements, we are ready to begin the creation of the visualization. This is essentially a graph drawing problem, as we wish to obtain a layout of the cluster nodes and corresponding neighborhood nodes that represents the relationship cluster. It is important to make the resultant drawing meaningful. Some desired characteristics in our work are that related wear particle measurements should be close to each other and highly related data should be even closer together.

From the simulations, the data in the output layer of the system (i.e., the data available for analysis) is arranged in two dimensions, as stated earlier. In fact, the spatial location of an output neuron in the topographic map corresponds to a particular domain or feature of the input data. Thus, it can be said that nearby nodes represent similar clusters. In other words, (as per actual scenario), the neural network model is trying to associate input patterns with common features to the same (or nearby) output node.

The system allows the investigator to perform a relationship network analysis by providing data visualization feature. This feature uses the technique as mentioned above and is also discussed in [20]. Using this technique a network of the similar wear particle and its associations can be built incrementally starting with the very first clue available. This helps in broadening the research and investigation domain without going into vague areas. Figure 3 shows a sample of the visual appearance of the mapped data. Each cell can contain more than one wear particle measurement and hence the similar measurements are mapped in closer proximity. This compliments in identifying similar cases, as the six parameters become the detrimental part for the mapping of these cases. The cells are coded in the sense that the intensity of a color signifies the number of similar measurements contained in a

cell. The cells in the grid are selectable where clicking a cell opens up the details of the wear particle information contained in the database.

Evolution: There are two time-dependent parameters, n and N , in the learning rule of Kohonen network: the learning parameter n determines what fraction of the distance to the input vectors will be moved, and the neighbor parameter N that determines the size of the neighborhood around the closest output vector within which other output vectors will be adjusted. Both n and N depend on t , the number of learning steps already performed. Ordinarily, these are constructed to be decreasing functions of t such that the network's response during learning will decrease over time; the network thus rigidifies and stabilizes at a solution. Thus, in order to assure confidence in the resulting wear modes of the particles, the no. of input vectors (i.e., the no. of wear particle experiments forming a database) shall be large enough for training of the Kohonen network. In turn, this tends to provide insight into evolution of the relationship cluster. Each time a relationship cluster in the diagram is drawn, the position of each node is stored. When the next diagram is drawn, the previous layout is used as a starting point so that the resultant drawing differs only slightly. This helps to preserve the mental map of the diagram as it evolves. If a diagram is generated each time the underlying relationship changes, then all of these diagrams can be pieced together to form an animation of the evolving relationship cluster. This can lead to better judgment on the current state of wear mode of the machine, and can also predict future state of wear particle if cluster size is large and number of subsequent experiments forming evolution is sufficient.

V. CONCLUSIONS

The case studies to enrich evolving database will undoubtedly allow us to build a library of normal and abnormal relationships of system parameters of wear particle to develop disjoint clusters. Accurate diagnostics for machine life prediction will only follow from a wealth of this type of multi-variant relationship monitoring histories. The proposed system provides a platform on which to implement and refine the diagnostic and visualization techniques required to achieve accurate prediction of remaining machine life.

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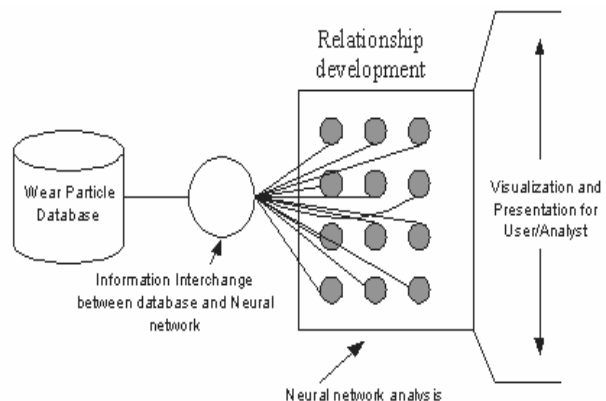


Fig. 2 Wear Particle Analysis System using neural network

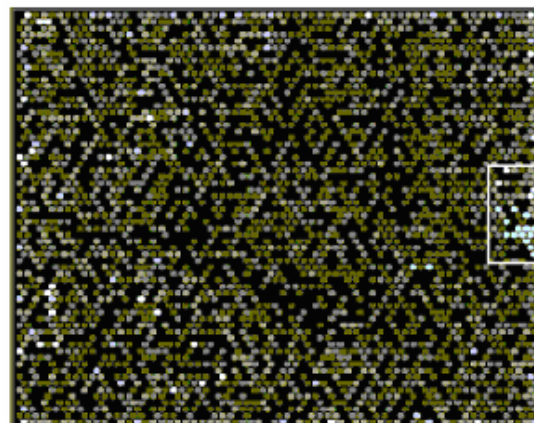


Fig. 3 Overlaying of Cells for visualization; brighter the cell, higher the frequency of similar wear