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Self-Tuning Varri Method in Preparing Fatigue Segment

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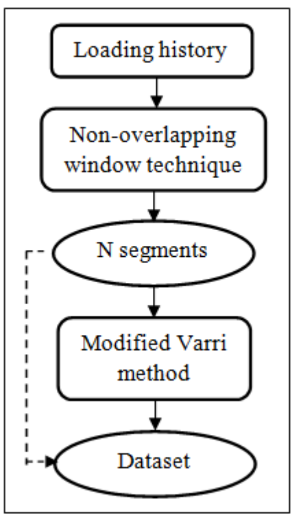
Graphical abstract



Abstract

An overlapping segmentation method on time series data is often used for preparing training dataset i.e. the population of instance, for classification data mining. Having large number of redundant instances would burden the training process with heavy computational operation. This would happen if practitioners fail to acknowledge an appropriate amount of overlap when performing the time series segmentation. Fortunately, the risk could be decreased if knowledge preferences can be determined to guide on overlapping criteria in the segmentation algorithm. Thus, this study aims to investigate how the Varri method is able to contribute for better understanding in preparing training dataset consists of irredundant fatigue segment from the loading history (fatigue signal). Generally, the method locates segment boundaries based on local maxima in the difference function which are above the assigned threshold. In the present study, the mean and standard deviation have been used to define the function due to the fact that predicting attributes are the key components in defining instance redundancy. The resulting dataset from the proposed method is trained by three classification algorithms under the supervision of the Genetic algorithms-based feature selection wrapper approach. The average performance index shows an additional advantage of the proposed method as compared to the conventional procedure in preparing training dataset.

Keywords: Fatigue segment; fatigue signal; classification; segmentation; Varri method

Abstrak

Kaedah peruasan bertindih kerap digunakan ke atas siri masa untuk menyediakan set data latihan i.e. populasi sampel, untuk pengelasan perlombongan data. Namun begitu, kegagalan menentukan jumlah pertindihan yang sesuai mengakibatkan saiz set data yang terhasil terlalu besar. Ini amat tidak diingini dalam perlombongan data kerana proses latihan terbeban akan operasi pengiraan yang berat. Walau bagaimanapun, risiko pertindihan data dapat dikurangkan sekiranya keutamaan pengetahuan ditentukan untuk memahami kriteria pertindihan dalam algorithma peruasan. Justeru, kajian ini bertujuan untuk menyelidik bagaimana kaedah Varri dapat menyumbang kepada pemahaman yang lebih baik dalam penyediaan data (segmen) dari sejarah beban (isyarat lesu) terikan. Secara umum, kaedah Varri menentukan titik-titik sempadan segmen data berdasarkan nilai maksimum setempat fungsi perbezaan. Dalam kajian ini, fungsi perbezaan Varri diformulasi oleh statistik purata dan sisihan piawai segmen yang mana kedua-duanya komponen penting dalam definasi data lewahan. Set data terhasil daripada kaedah yang dicadangkan dilatih oleh tiga algorithma pengelasan di bawah penyeliaan pendekatan balutan pemilihan pembolehubah teras algoritma genetik. Purata indeks pretasi menunjukkan kelebihan berganda kaedah yang dicadangkan berbanding prosedur konvensional dalam menyediakan set data latihan.

Kata kunci: Segmen lesu; isyarat lesu; pengelasan; segmentasi; kaedah Varri

■1.0 INTRODUCTION

A learning algorithm generally provides a classification model once a training dataset is processed. Training dataset is a collection of training examples known as instances. Each instance has a vector of predicting attributes and a categorical output. One of the ways to accelerate the learning session and to avoid excessive storage is by reducing the instances (redundant or duplicate instances) of such an original dataset. Apart from the advantages, the reduced dataset is less contaminated with noise and has low risk of over-fitting, and these lead to the improved generalization accuracy[1]. An issue of redundant instances may occur when all available instances from its origin e.g. image, text, time series, etc are considered in an initial dataset. It is regarded as adhering to the assumption that the more the merrier, which is applicable in the classification data mining, despite the fact that it is not always the truth. In a case when presenting the time series segment as an instance, a misuse of overlapping window technique would easily populate the dataset with too many duplicate instances despite the fact that the dataset size is large.

A generic idea of time series overlapping window segmentation is to undergo windows operations along a given time series, in order to generate a finite number of time series segments in which two adjacent segments are overlapped. An amount of overlap (or also referred as an overlapping rate) can be fixed or an overlap can vary with the existence of specific behaviors. In a case when a segment is an instance, then the size of the dataset is said to be relative to the number of segments given by the segmentation technique. Under an assumption concerning segments of the same length, the largest collection of segments can be found when mutual overlap of the windows corresponding to two adjacent segments occurs at maximum overlapping rate i.e. $(w/w-1)$ where w denotes window length[2]. Under this condition, the corresponding dataset has reached its maximum capacity which is tailored to the basic need of data mining[3], though it is probably full of redundant samples. Moreover, it does not strictly conform to the condition of an ideal dataset. Even that condition can be satisfied using the traditional data reduction approach[4], other than the fact that the time complexity when operating the clustering method[5] for example is considered impractical. Conversely, having a minimum rate (0%) of the time segmentation provides the dataset with a collection of non-overlapped adjacent segments that completely spans the time series. At this point segments are clearly free from redundant issue (considering random behaviour of time series) but it provides less number of instances for training. To obtain a balanced dataset directly from the time series overlapping the window segmentation algorithm a modified version of the Varri method can be applied, where the amount of overlap is determined based on measuring the different functions of G.

The function G calculates the difference of feature(s) in two successive sliding windows that moves along the given time series. In the original form of Varri method the G function is composed of a frequency measure (first feature) $F_{dif} = \sum_{i=1}^{w}|x_i - x_{i+1}|$ and amplitude measure (second feature) $A_{dif} = \sum_{i=1}^{w}|x_i|$ where x_i is the i^{th} data point then the G function of j^{th} window is defined as:

$$G_i = k_1\left|A_{dif,i+1} - A_{dif,i}\right| + k_2\left|F_{dif,i+1} - F_{dif,i}\right|;\ j = 1 \ldots N-1 \tag{1}$$

where k_1 and k_2 are coefficients for amplitude and frequency measures respectively and N is the number of windows in analysis[6]. A local maximum in the function G which is beyond the specific threshold specifies the boundaries of segments[7]. Different applications desire specific features in defining the function G in which the resulting segments are parallel to user's segmentation goals. References[8-9] use a fractal dimension as feature of function G for detecting epileptic patterns. Meanwhile Azami *et al*.[7] apply standard deviation and variable threshold in their extended version of different function. In the instance reduction phase, the predicting attributes are commonly referred by the cluster-based reduction method e.g. *k*-means where cluster centroids (or with several other cluster representatives) are kept for training session. Thus, in the present study two attributes namely mean and standard deviation are chosen to define the G function in the Varri method. Those attributes are empirically proven to be the most significant statistical parameters (out of eight parameters) in our fatigue segment classifier i.e. assigning low or high damage label to the fatigue segment[10-11]. Unlike the mean, standard deviation is not a primary parameter in mechanical fatigue domain studies[12] but it starts gains popularity since it plays a major role in classifying fatigue segment.

A dataset obtained from the proposed method is learned using three classification algorithms. The rationale behind the algorithm selection lies in the fact that each algorithm implements different learning concepts thus reducing learning bias[13]. In order to let each of the learning algorithms choose the relevant subset of features, the Genetic algorithm-based feature selection wrapper approach is used. All learning was performed under the 10-fold cross validation framework in order to control bias. As a result, each run holds 10 performance indices where their average value was referred. Results are compared to a conventional dataset which is the output of a combination of maximum-overlapping window segmentation and *k*-means clustering algorithm. In a case that the dataset obtained from the proposed method is underperformed in all occasions, the trade-offs between training cost and predictive accuracy show that the proposed method still has beneficial effects (i.e. no requirement for data reduction algorithms and provides less complexity in learning).

2.0 MATERIALS AND METHODS

2.1 Loading History

The fatigue loading history is one branch of the time series family in which the strain value is measured against time interval. In the present study, four secondary loading histories were measured on the front lower suspension arm of a mid-sized sedan at various driving speeds and in a normal traffic environment, i.e., on public roads. Two different behaviors of the data representing road conditions have been considered. Firstly, the road load conditions of a stretch of paved road represent primarily consistent load features containing noise, while an on-campus road represents load features that might include turning and halting, rough road surfaces and speed bumps. The strain value incorporated in the signal was recorded at a single location (a point that received maximum stress) using a strain gauge with the sampling rate of 500Hz. The material for the lower suspension arm is SAE1045 steel, and this material's specifications are used in our fatigue damage calculation. A union of the segmentation output with respect to the recorded histories represents a training dataset.

2.2 Fatigue Damage

In the fatigue analysis, fatigue damage D is naturally obtained by finding a reversal value of fatigue life Nf. For strain-controlled loading history, life estimation can be done through solving strain-life models, in which both elastic and plastic cyclic behaviours of a material are described by two nonlinear functions; ε_{ea} and ε_{pa} those functions are comprehensively defined in the Smith Watson Topper (SWT) model as follows:

$$\sigma_{\max}\varepsilon_a = \sigma_{\max}\left(\varepsilon_{ea} + \varepsilon_{pa}\right) = \frac{\left(\sigma'_f\right)^2}{E}\left(2Nf\right)^{2b} + \sigma'_f\varepsilon'_f\left(2Nf\right)^{b+c} \tag{2}$$

where σ_{max} is a maximum stress of fully reversed cycle derived from Basquin's relation, and ε_a is the total strain amplitude. Material coefficients σ'_f, E, ε'_f, b and c are given as fatigue ductility coefficient, elastic modulus, fatigue strength coefficient, fatigue strength component and fatigue ductility exponent. By inversely solving the SWT model the corresponding total damage TD value for a given M length loading history can be easily computed using the following Palmgren-Milner rule:

$$TD = \sum_{i=1}^{c} D_i = \sum_{i=1}^{c} \frac{1}{Nf_i} \tag{3}$$

where c is the total number of strain-stress cycles underlying the loading history. For labeling purpose, a fatigue signal or fatigue segment is conveniently delineated between low-damage (high-cycle) and high-damage (low-cycle) fatigue regimes where the transition life of strain curve is referred. Related to SAE1045 steel the boundary point is equal to 10^3 repetitions (equivalent to 10^{-3} in damage).

2.3 Proposed Method

Proposed time series segmentation method is a two-stage procedure that is illustrated in Figure 1. Firstly, the 0% overlapping (non-overlapping) window technique is applied on the time series i.e. fatigue loading history. This step will generate around $N = floor(M/w)$ segments where $floor(\quad)$ rounds the value towards minus infinity. Consequently, the dataset is now filled up with segments which are not only completely different in terms of data sequence but also in peak-valley (PV) representation, this is due to random behaviour of fatigue signal[14]. Notice that, wider the window used less number of segments will be generated in a case of constant M. In addition there is no application constraint if filter analysis is used in prior to smooth the signal.

In the second stage, our version of the Varri Method is applied to the current dataset in order to generate additional irredundant instances. Consider S_i and S_{i+1} are two adjacent segments from the first step and let $F1$ and $F2$ are an independent sliding window in S_i and S_{i+1} respectively. Both windows are permitted to have length in range of $[1, w-1]$ but must satisfy the requirement of $|F1| + |F2| = w$ at all times. In addition an endpoint and a starting point of S_i and S_{i+1} must be an endpoint of $F1$ and a starting point of $F2$. A joint combination of $F1$ and $F2$ is actually a segment of length w that overlaps S_i and S_{i+1} by $(|F1|/w)\%$ and $(|F2|/w)\%$ respectively. Thus, the introductory of $F1$ and $F2$ already satisfy both overlapping window concept and basic requirement of the Varri method. For $j = 1 \ldots w-1$ the difference measure function G_j is computed as follows:

$$G_j = a_j\left(\left|\frac{mean(F1_j \cup F2_j)}{mean(S_i)}\right| + \left|\frac{std(F1_j \cup F2_j)}{std(S_i)}\right|\right) + \ldots \\ + b_j\left(\left|\frac{mean(F1_j \cup F2_j)}{mean(S_{i+1})}\right| + \left|\frac{std(F1_j \cup F2_j)}{std(S_{i+1})}\right|\right) \quad (4)$$

where $F1_j = \{x^k_{S_i} : w - j + 1 \le k \le w\}$ is the sequence of j data points and $x^k_{S_i}$ shows k^{th} data point in segment S_i. Meanwhile $F2_j = \{x^k_{S_{i+1}} : 1 \le k \le w - j\}$ is the sequence of $w - j$ data points and $x^k_{S_{i+1}}$ shows k^{th} data point in segment S_{i+1}. Let coefficients a_j and b_j be proportional to the width of sliding window subject to S_i and S_{i+1}. In this study, we simply let $a_j = 1/j$ and $b_j = 1/w - j$. In other words, an influence of the first (second) outer parentheses in G becomes larger when an initial (end) point of sliding window $F1(F2)$ is approaching the first (last) data point of $S_i(S_{i+1})$. The maximizing argument of $\max_{1\le j\le w-1}(G_j)$, states that, j^* determines the best connecting point between $F1$ and $F2$ thus a new instance at iteration i is found by putting $F1_{j^*}$ and $F2_{j^*}$ as one successive segment. By completing stage 2 for $N-1$ iterations i.e. $i = 1 \ldots N-1$ size of dataset grows up to $N + (N+1)$.

2.4 Performance Assessment

The new method proposes a direct mechanism i.e. avoiding the use of data reduction method, to generate the reduced training dataset in particular when having a segmental time series as the training instance. In order to evaluate how reliable the method is, its corresponding dataset is compared to the dataset generated via the conventional approach in terms of the classification accuracy. To eliminate improper assessment of the accuracy, due to the possibility of having a class imbalance, a recent Generalized Index of Balanced Accuracy (IBA) was used. The IBA measure is derived as follows:

$$IBA_\alpha(A) = (1 + \alpha.Dm)A \quad (5)$$

where dominance factor Dm is used to evaluate the difference of two metrics, *Sensitivity* and *Specificity*, derived as follows:

$$Dm = Sensitivity - Specificity = \frac{TP}{TP+FN} + \frac{TN}{TN+FP} \quad (6)$$

where TP (true positive), FP (false positive), FN (false negative) and TN (true negative). Accuracies for both positive and negative classes are becoming more balanced when the Dm is closer to zero. The plain agreement about the selection of α value is dependent on the metric A used. As proposed in Garcia *et al.*[15], we employ

$$A = G_{mean} = \sqrt{Sensitivity - Specificity} \text{ with } \alpha = 0.1 \quad (7)$$

Prior to performance assessment, every instance was embedded with initial eight statistical parameters[11] and was labeled with low (or high) damage class. Three kinds of classification algorithm namely k-nearest neighbors (*k*-NN), artificial neural network (ANN) and decision tree (Tree) were utilized since they approach the training dataset in a specific pedagogy. To enable the learning algorithm to select a proper subset of predicting attributes, the learning session was executed in the environment of Genetic algorithm-based wrapper feature selection approach (GAWFS)[16].The configuration parameters of GAWFS are given as follows: population size = 1000, (8+1) bits binary chromosome, tournament selection method with size of 2, one-point crossover with probability of 0.9 and simple mutation with probability of 5% while learning parameters of tested algorithms are default settings as implemented in WEKA®[17]. The 10-fold cross validation framework was used as an aid to control for bias. As a result, each run holds 10 performance indices where their average value was referred. All the experiments are executed on self-coding programs using Matlab7 software. Finally, best model from each combination then learnt to classify 160 unseen samples in which 40 segments were generated randomly from each loading history.

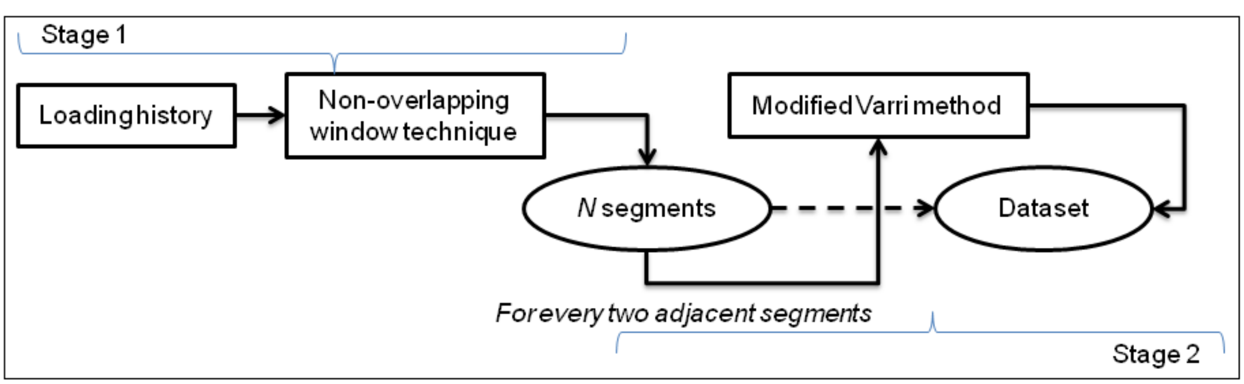


Figure 1 The proposed method for training dataset preparation

3.0 RESULTS AND DISCUSSION

Representing the resulting argument, with respect to the local maxima of the G function in the form of empirical cumulative distribution function (empirical CDF), it has revealed the fact that around 75% of segments from both D1 (Figure 3a) and DD (Figure 3b) have an amount of overlaps less than 0.6 (Figure 2a). As for the campus road (Figure 2b), over 40% of two adjacent segments, either from D3 (Figure 3c) or DA (Figure 3d) are overlapped, not less than 0.4. The dissimilarity on the percentages indicates that a poor quality of population might be obtained if one simply considers a fixed-rate strategy along the segmentation operation for both types of road conditions. To wit, on all loading histories, the maximum overlapping rate of one half of the segments experience lies in the range of 0.4 to 0.5 (refers the dash lines in Figure 2a-b).

Figure 4 shows the class distribution of fatigue segments gathered from the modified Varri method compared to the benchmark dataset (obtained from the clustering reduction method), for the four loading histories. Each bar represents the total number of segments with respect to the stated signal by summing up both numbers of class members. For the proposed method, a similar amount of samples (117 segments) is found across all histories. This result is somewhat expected, since each history is initiated with a similar number of non-overlapping segments. In contrast, the cluster analysis determines which and how many segments should be placed from such respective loading history into the dataset. Nevertheless, in both methods, it is apparent that the D1, D3 and DA history are highly populated (around 90%) with low damage segments. This pattern concurs with the nature of loading history[18], that the number of low fatigue cycles outperforms high damage cycle in most occasions. Contrary to the above pattern, consistency in the strain value along the time interval and a wide gap between maximum and minimum values have been noticeable, making the DD results differ. On the whole, the proposed method generates 36% more samples than the benchmark and based on the class ratio, both are assigned as a low class imbalance dataset.

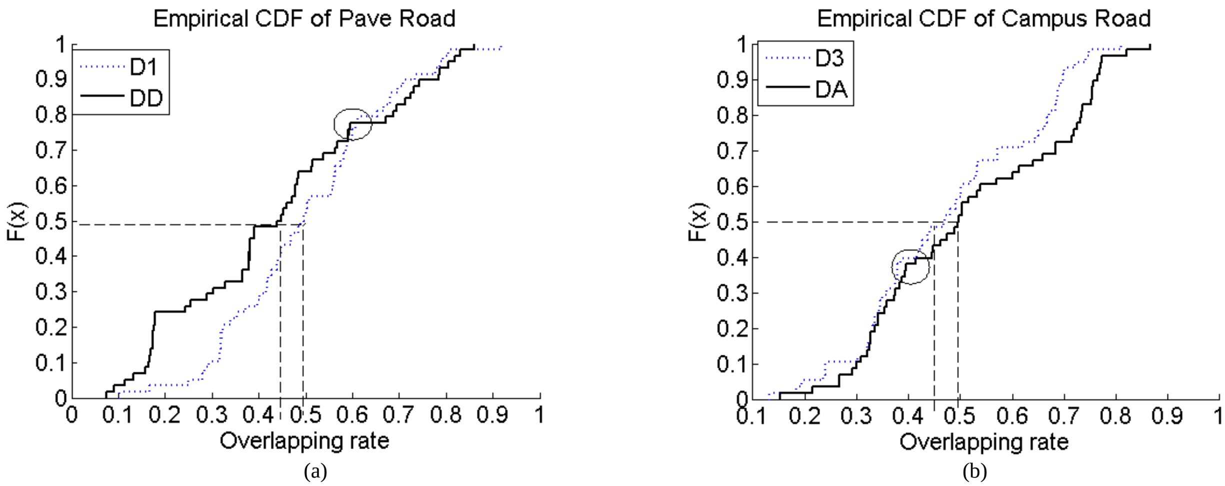


Figure 2 An empirical cumulative distribution (CDF) of the maximizing argument corresponds to the G function for two road conditions; a) Pave road and, 2) Campus road

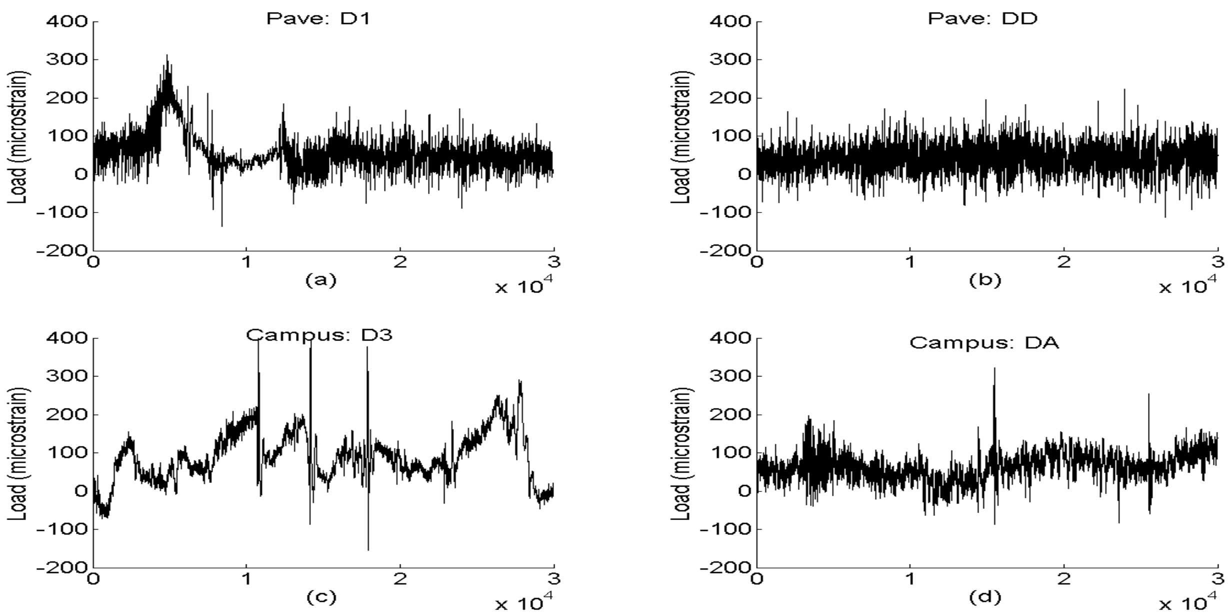


Figure 3 Four experimental loading histories from two different road terrains

The training results presented in Table 1 are obtained from *k*NN, ANN and Tree which are executed using the GAWFS. To read, for example in the benchmark dataset, the first row in the main body tells us that the optimal feature subset corresponds with the *k*NN consisting of A4, A5, A6 and A10. The use of that subset as predicting attributes records the IBA measure at the value of 0.9818 on average. Overall, attributes A7 and A13 appear to be the most irrelevant attributes to the domain of the study. Similarly, A6 and A8 seem insignificant on one side of the datasets across all algorithms. Since they appear in nearly all combinations, it is encouraging to declare A5 and A10 as the most meaningful attributes for the fatigue segment classifier based on the time domain statistical parameters. This finding is consistent with our previous works[10-11] which has found that standard deviation has the capacity to be more pronounced in the fatigue damage analysis. Considering the learning algorithms used have selected their best feature subset, it is apparent that all algorithms achieve better performance on the benchmark dataset. However, the Friedman test indicates that there is no significant difference (p-value = 0.033, significance level of 0.05) between the mean performances of the two datasets. Finally, over 160 unknown testing samples (balanced class distribution testing dataset), the combination of kNN and the proposed dataset have recorded the highest accuracy (where they classify about 133 samples correctly) whereas others' performance is considerably good (assuming that the par value at 80%).

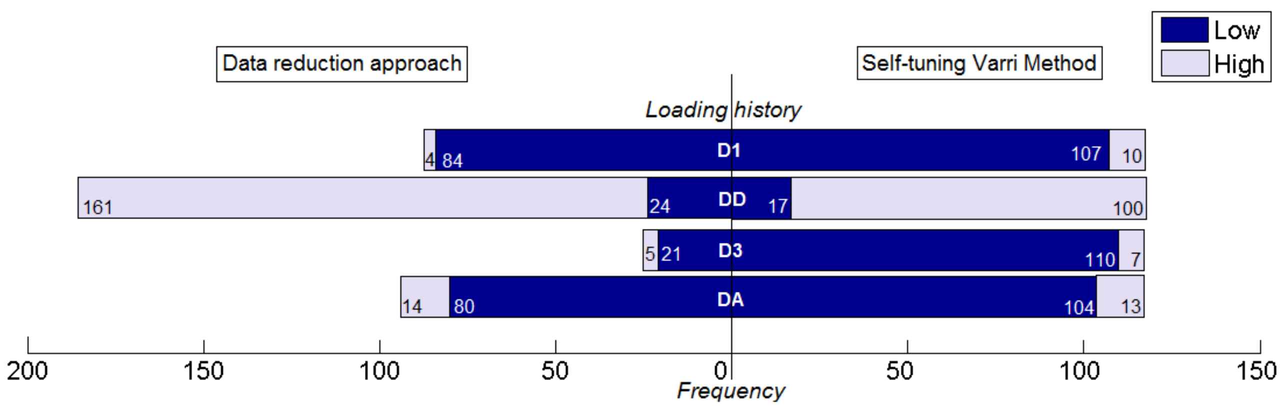


Figure 4 Comparison on the sample distribution between the conventional approach and the proposed method

Table 1 Experiment results of both datasets consists of an optimal attribute subset, IBA measures and predictive accuracies

Dataset	Algorithm	Attribute (A)[a]														IBA[b]	Accuracy (%)
		1	2	3	4	5	6	7	8	9	10	11	12	13	14		
Benchmark	*k*NN	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0.9818	86.78
	ANN	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0.9592	86.78
	Tree	1	1	1	0	0	1	0	0	1	1	1	1	0	1	0.9762	85.63
Proposed	*k*NN	0	0	0	1	1	0	0	1	1	1	0	0	0	0	0.9624	89.00
	ANN	1	0	1	0	1	0	0	1	1	0	1	1	0	0	0.9023	86.66
	Tree	1	1	1	1	1	0	0	1	0	1	0	1	0	1	0.9402	82.18

[a] Attribute list follows a statistical sequence discussed in the Materials and Methods section.
[b] IBA measure is represented by an average value over 10 runs.

4.0 CONCLUSION

This paper provides a comparative study on the training dataset preparation for binary-class fatigue segment classification problem. The results from this study suggest that the application of the Varri method to time series segmentation is a useful reliable tool for providing a quality dataset, just as we would expect from the conventional procedure. The finding provides a direct mechanism to generate a set of irredundant fatigue segments from the loading history without needing any filtering tool e.g. clustering. In addition, the difference measure function of the proposed Varri method is adjustable, depending on the users' definition of redundant samples. Moreover, a dataset resulted from the proposed method has reputedly wider data coverage i.e. higher prediction accuracy. Despite the fact that the study is limited by the number of loading history, it is interesting that further research could be undertaken using loading that is recorded off-road.

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References

[1] Czarnowski, I. and P. Jędrzejowicz. 2006. Instance Reduction Approach to Machine Learning and Multi-Database Mining. *Annales UMCS Inform. AI*. 4: 60–71.

[2] Niamut, O.A. and R. Heusdens. 2005. Optimal Time Segmentation for Overlap-Add Systems with Variable Amount of Window Overlap. *Signal Processing Letters, IEEE*. 12(10): 665–668.

[3] Brain, D. and G. Webb. 1999. On The Effect of Data Set Size on Bias and Variance in Classification Learning. Proc. 4th Australian Knowl. Acquis. Workshop. 117–128.

[4] Albalate, M.T.L., Data Reduction Techniques in Classification Processes. 2007. Ph. D., Llenguatges I Sistemses Informatics, Universitat Jaume I.

[5] Niyogi, P. and N. Karmarkar. 2000. An Approach to Data Reduction and Clustering with Theoretical Guarantees. Proc. Int. Conf. Machine Learning. 679–686.

[6] Vaari, A., Digital Orocessing of The EEG in Epilepsy, 1998, Licentiate Thesis, Tampere University of Technology, Tempere, Finland.

[7] Azami, H., K. Mohammadi and B. Bozorgtabar. 2012. An Improved Signal Segmentation Using Moving Average and Savitzky-Golay Filter. *J. Signal Inf. Process*ing. 3(1): 39–44.

[8] Kirlangic, M.E., D. Perez, S. Kudryavtseva, G. Griessbach and G. Henning. 2001. Fractal Dimension as a Feature for Adaptive Electroencephalogram Segmentation in Epilepsy. 2001 Proc. 23rd Annu. EMBS Int. Conf. 2: 1573–1576.

[9] Anisheh, S.M. and H. Hassanpour. 2009. Adaptive Segmentation with Optimal Window Length Scheme Using Fractal Dimension And Wavelet Transform. *Transactions B: Applications*. 22(3): 257–268.

[10] Nopiah, Z.M., M.H. Osman, S. Abdullah and M.N. Baharin. 2011. The Identification of Low Fatigue Damage Using Fuzzy Double Clustering Framework. 2011 IEEE 7th Int. Colloq. Signal Processing and its Applications. 181–186.

[11] Osman, M.H., Z.M. Nopiah and S. Abdullah. 2012. Feature Selection for Fatigue Segment Classification System Using Elitist Non-dominated Sorting in Genetic Algorithm. *Appl. Mech. Mater*. 165: 232–236.

[12] Nopiah, Z.M., M.I. Khairir and S. Abdullah. 2008. Segmentation and Scattering of Fatigue Damage Time Series Data by Kurtosis And Root Mean Square. Proc. 7th WSEAS Int. Conf. Signal Process. 64–68.

[13] Kotsiantis, S.B. 2007. Supervised Machine Learning: A Review of Classification Techniques. *Inform*. 31: 249–268.

[14] Nopiah, Z.M., M.N. Baharin, S. Abdullah, M.I. Khairir and A. Ariffin. 2010. Running Damage Extraction Technique for Identifying Fatigue Damaging Events. *WSEAS Trans. Math*. 9(5): 324–333.

[15] García, V., J.S. Sánchez and R.A. Mollineda. 2012. On The Effectiveness of Preprocessing Methods When Dealing with Different Levels of Class Imbalance. *Knowl-Based Syst*. 25(1): 13–21.

[16] Karegowda, A.G., M.A. Jayaram and A.S. Manjunath. 2010. Feature Subset Selection Problem Using Wrapper Approach in Supervised Learning. *Int. J. Computer Applications*. 1(7): 13–17.

[17] Hall, M., E. Frank, G. Holmes, B. Pfahringer, P. Reutemann and I.H. Witten. 2009. The WEKA Data Mining Software: An Update. *SIGKDD Explor. Newsl*. 11(1): 10–18.

[18] Stephens, R.I., P.M. Dindinger and J.E. Gunger. 1997. Fatigue Damage Editing for Accelerated Durability Testing Using Strain Range and SWT Parameter Criteria. *Int. J. Fatigue*. 19(8–9): 599–606.