Journal of
Data Acquisition and Processing

ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.777639

ID-639: FEATURE EXTRACTION OF INDICATOR CARD DATA FOR SUCKER-ROD PUMP WORKING CONDITION DIAGNOSIS USING MACHINE LEARNING.

.

Dr. Priya Pise
Professor & Head, Department of AI&DS, Indira College of Engineering and Management, Pune, India, priya.pise@gmail.com

Mr. Ashish Dudhale,
Department of Electronics and Telecommunication Engineering, Research scholar, JJT University, Rajasthan, India and Assistant Professor, AIT, Dighi, Pune, India
ashish.dudhale@gmail.com

Dr. Nilesh Uke
Professor, Trinity Academy of Engineering, Pune, India
nilesh.uke@gmail.com

Dr Akhilesh Kumar Mishra,
Research Guide, JJT University, Rajasthan, India
agars2012@yahoo.in

Abstract

Our Research “Feature Extraction of Indicator Card Data for Sucker-Rod Pump Working Condition Diagnosis using Machine Learning” is a three feature extraction techniques for sucker-rod pump indication card data based on Fourier Descriptors (FD), Geometric Moment Vector (GMV), and Grey Level Matrix Statistics (GLMX) have been investigated, simulated, and compared. The Geometric Moment Vector algorithm is more time-consuming and requires more memory space, while the Grey Level Matrix Statistics algorithm provides low-dimension feature vectors with more running time. Numerical experiments show that the Fourier Descriptors algorithm requires less running time and less memory space with the possibility of information loss due to non-optimal numbers of Fourier Descriptors. As well as extra memory. Additionally, the Fourier Descriptors approach and the Geometric Moment Vector algorithm's rotational invariance property may lead to incorrect pattern identification of indicator card data when utilised for sucker-rod pump operating condition diagnostics.

Key: Feature, Extraction, Indicator, Card Data, Sucker-Rod, Pump, Working, Condition, Diagnosis, Machine Learning.

Introduction

The most popular artificial lift method for onshore oil well production is the sucker-rod pump system [1-3]. Sucker-rod pumps are used to produce oil in around 80% of wells worldwide and 90% of those in China [4, 5]. A sucker-rod pump system requires expensive and time-consuming maintenance and optimization. The relation curve between the load and the displacement of a sucker-rod pump in an unbroken suck cycle is the indication card [6], where the -axis denotes displacement and the -axis the load.

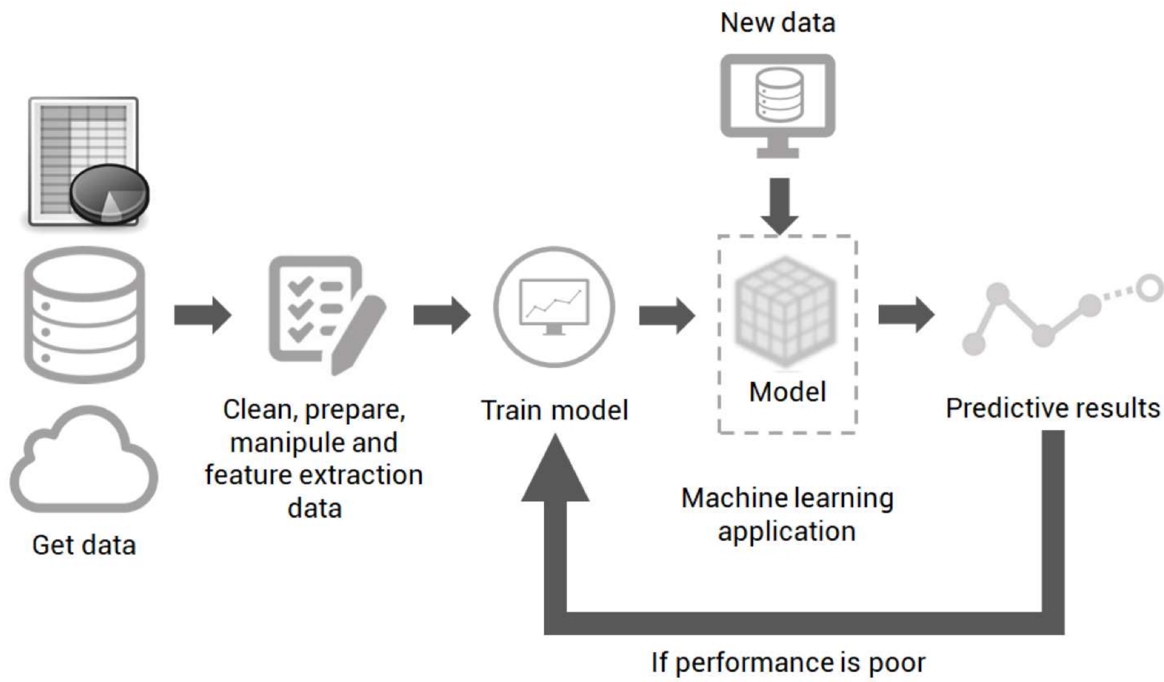

Fig.1: Feature Extraction of Indicator Card Data for Sucker-Rod Pump Working Condition Diagnosis using Machine Learning Flow.

The indication card is useful for analysing the sucker-rod pump wells' down-hole operating conditions [7], as it can assess the well's operational state and offer trustworthy evidence of high efficiency, acceptable exploitation for oil well output. The card can display a form that may represent a regular functioning or a failure scenario when the system is in use. The pattern identification and fault diagnostic techniques are used to recognise certain distinct curve forms, pinpoint which sort of abnormal scenario is present, and explain why the problem arises [8] based on various types of real-time indicator card data. Therefore, it is crucial to accurately and quickly identify the sucker-rod pump indication card in order to diagnose any problems with the down-hole operating condition.

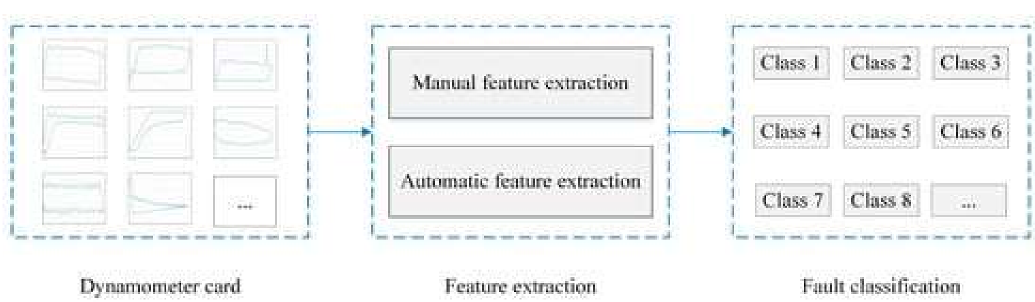

Fig.2: Feature Extraction of Indicator Card Data for Sucker-Rod Pump Working Condition Diagnosis using Machine Learning Method.

Sucker-rod pump operating state automated fault diagnosis is a visual interpretation procedure [9]. The old interpretation techniques are no longer appropriate for automated fault identification of down-hole situations. In order to increase the precision and effectiveness of sucker-rod pump system defect detection, a number of signal processing techniques, including artificial neural network (ANN) [10] and fuzzy support vector machine (FSVM) [11], have been researched and used to pattern recognition of indicator cards.

Algorithm Based on Fourier Descriptors

A common technique for picture reconstruction and classification is the Fourier transformation. The Fourier Descriptors (FD), which represent the form of the object in the frequency domain, are generated as a full set of complex numbers [16].

The superfluous indication card points (data) are removed using the polygonal approximation approach to lessen the computational complexity. The steps are listed below.

In order to choose the feature pixels (data) of the polygon that satisfy the requirement with the highest curvature of a specified length curve, we first traverse all the digital pixels (data) of the indicator card curve in accordance with a given value, which is called.

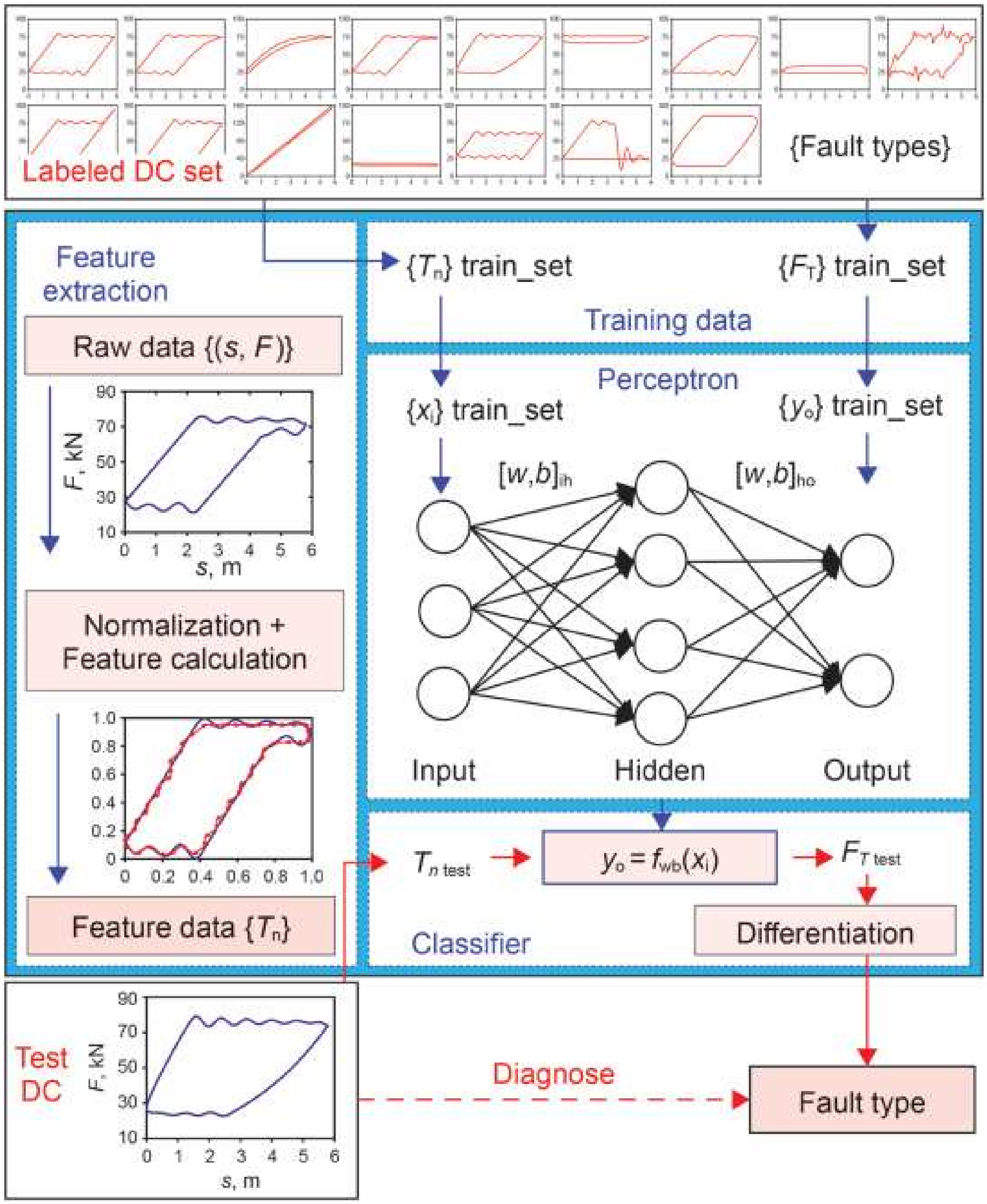

Fig.3: Feature Extraction of Indicator Card Data for Sucker-Rod Pump Working Condition Diagnosis using Machine Learning Process.

Secondly, we store those feature data to an array.

The given value () is assigned as 0.008 according to comparison of different computation procedures. Take the pump-on-touch fault as an example; 34 feature pixels (data) are extracted from the original 702 pixels. Figure 1 shows the reconstructed graphic curve of the pump-on-touch fault compared with the original one.

Algorithm Based on Geometric Moment Vector

In image processing field, Geometric Moment Vector (GMV) can be used as an important feature to represent objects due to its translation invariance, rotation invariance, and scale invariance.

Since the scanned image of indicator card is grayscale and the image outline is not smooth, it is necessary to preprocess the image by using linearization and refinement technology.

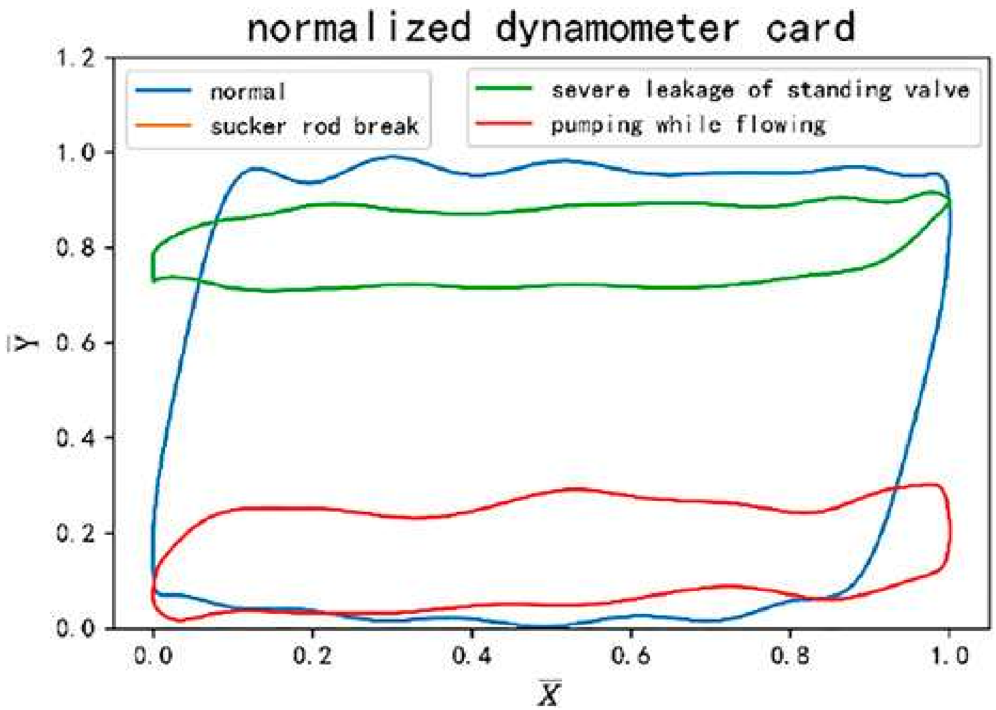

Fig.4: Feature Extraction of Indicator Card Data for Sucker-Rod Pump Working Condition Diagnosis using Machine Learning.

Results

One of the classic techniques for extracting visual features is the grid approach. The grid method's processing phases are listed below.

First, in the horizontal and vertical directions, respectively, we partition the picture of the indication card into a number of little grids of the same size and form. The grids that the indication card's curve travels through are then marked. Finally, we can get the indication card image's feature parameters.

In this study, we employ the grid-based Grey Level Matrix Statistics (GLMS) feature extraction approach.

The indication card curve should be transformed into a grayscale visual matrix prior to the GLMS feature extraction. The GLMS feature extraction algorithm has the following phases.

The mesh of grayscale matrix is initialized: if a grid is traversed by the indicator card curve, then the gray value is assigned as “1”.

According to the gray contour principle, other grids are assigned as such gray value: if the grid is located at the inside of the curve, then the gray value is equal to the initial value plus for its grids distance away from the curve; if the grid is located at the outer region of the curve, then the gray value is equal to the initial value minus for its grids distance away from the curve.

Conclusion

Three alternative feature extraction techniques, each based on a different Fourier descriptor, geometric moment vector, and grey level matrix statistic, have been examined and simulated in this article. The GMV algorithm is more time-consuming and memory-intensive due to different numbers of FDs, whereas the GLMS algorithm produces low-dimension vectors with good performance of speed and space. Numerical experiments demonstrate that the FD algorithm is with high computing speed and more memory space but possible loss of information.

When employed for sucker-rod pump operating condition diagnostics, the rotational invariance property of the FD method and the GMV algorithm may result in inaccurate pattern identification of indicator card data. For greater performance, more study on feature extraction from indicator card data has to be done.

References

1. G. P. Schirmer, J. C. P. Toutain, and J. C. Gay, “Use of advanced pattern recognition and knowledge-based system in analyzing dynamometer cards,” *SPE Computer Application*, vol. 3, no. 6, pp. 21–24, 2022.
2. L. Alegre and C. Morooka, “Intelligent diagnosis of rod pumping problems,” in *Proceedings of the 68th Annual Technical Conference*, vol. 3, pp. 97–108, SPE,2022.
3. G. Han and X. Wu, “Application of dynamometer card identification in diagnosis of working-condition for suck rod pump,” *Oil Drilling & Production Technology*, vol. 25, no. 5, pp. 70–74, 2019.
4. H. Tripp, “A review: analyzing beam-pumped wells,” *Journal of Petroleum Technology*, vol. 41, no. 5, pp. 457–458, 2021.
5. G. Nazi and J. Lea, “Application of artificial neural network to pump card diagnosis,” *SPE Computer Application*, vol. 6, no. 6, pp. 9–14, 2021.
6. M. J. Gao, “Portable intelligent instrument for pumping data collection,” *Journal of Transducer Technology*, vol. 24, no. 9, pp. 58–62, 2015.
7. F. Barreto and M. Tygel, “Automatic down-hole card generation and classification,” in *Proceedings of the SPE Annual Technical Conference*, pp. 311–318,2019.
8. Z. Pan and J. Ge, “An adaptive neural network for identification of dynamometer card,” *Acta Petrolei Sinica*, vol. 17, no. 3, pp. 104–109, 1996.

9. R. Dickinson and J. Jennings, "Use of pattern-recognition techniques in analyzing down-hole dynamometer cards," *SPE Production Engineering*, vol. 5, no. 2, pp. 187–192, 1990.

10. D. Baodong and L. Mingshan, "Analyzing dynamometer card of well pumping by using artificial nerve network method," *Well Testing*, vol. 7, no. 1, pp. 27–29, 1998.
11. W. Shi and J. Dai, "FSVM based recognition approach for down-hole pump dynamometer cards," *Oil Field Equipment*, vol. 33, no. 4, pp. 46–48, 2004.
12. W. Shoujue, "Bionic (topological) pattern recognition-a new model of pattern recognition theory and its applications," *Acta Electronica Sinica*, vol. 30, no. 10, pp. 1417–1420, 2002.
13. S. C. Yuan, "Simple distinguish way for dynamometer card," *Well Testing*, vol. 14, no. 1, pp. 49–50, 2015.
14. B. D. Du and M. S. Li, "Analyzing dynamometer card of well pumping by using ANN method," *Well Testing*, vol. 1, no. 7, pp. 27–29, 1998.
15. S. H. Yang, "Applications of difference curve methods in diagnosis of indicator diagram," *Petroleum Drilling Techniques*, vol. 30, no. 2, pp. 63–64, 2020.