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# Quantum Machine Learning For Failure Diagnosis: Analysis Of Different Quantum Encoding Methods

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Currently, with the growing focus on minimizing risks in production systems, the desire to understand and predict the machinery ecosystem has become a key factor (Barraza et al., 2022). In this context, rotating machines represent one of the main focuses of the search for more accurate failure predictions. In this sense, it appears that they are fundamental components in a variety of industries and play a crucial role in energy generation, manufacturing, transport, and many other applications (Loparo et al., 2000).

From this perspective, to predict the behavior of machines, provide the necessary information about the health status of components, and support maintenance decisions, Prognostics and Health Management (PHM) is widely used in the scientific and industrial community – mainly regarding monitoring and estimating the health conditions of an asset, taking vibration signals as an example (Maior et al., 2023). Regarding this monitoring, Machine Learning (ML) and Deep Learning (DL) Models are widely used. However, with technological advances, the area of Quantum Computing (QC) has been gaining strength among researchers and large companies and has also been growing rapidly on the world stage (Huang et al., 2020).

Despite hardware limitations, QC is a promising alternative to enhance existing ML algorithms and improve the computational efficiency of models in Prognostics and Health Management (PHM). Thus, our focus is to apply Quantum Machine Learning models for bearing failure modes diagnosis and to compare different quantum encoding methods. This study is an advance of the authors' prior work, e.g. see (Maior et al., 2023). The main contribution lies in the exploration of alternative encoding methods to identify the most effective one in bearing vibration analysis.

In this work, three encoding methods are employed: Angle Encoding, Amplitude Encoding and ZFeaturemap - each of them was used independently in the QML procedure (Date and Rath, 2023). In Angle Encoding, data is represented through angles in a quantum circuit - each component of the vector is mapped to a qubit, preserving the information. In the Amplitude Encoding procedure, the relationship between the number of qubits and the size of the state space is related to the concept of information entropy (Cuéllar et al., 2023). Shannon entropy, a measure of the amount of information contained in a system, is defined in terms of the base-2 logarithm of the number of possible states. For a system with $N$ possible states, the number of qubits is calculated as $\log_2(N)$. Additionally, ZFeaturemap is a quantum computing encoding technique that involves applying the $Z$ operator on qubits (Guo et al., 2022). This method aims to map specific data features to quantum states, introducing correlations that can be exploited in quantum machine learning algorithms.

The foundation of this study lies in the utilization of the public database from Case Western Reserve University (CWRU). This dataset comprises vibration measurements obtained from bearings exhibiting various types of failures, such as wear, cracks, and other defects. From these input data, features (mean, variance, root mean square, kurtosis, skewness, peak-to-peak, peak index, peak, standard deviation, power, maximum amplitude, minimum amplitude, form factor and crest factor) were extracted from the analyzed signal for later refined and dynamic use. Throughout this study, tests were conducted using input data with 5, 8, 10, and 14 of these features - aiming to assess potential changes in the measurement quality performed during the QML combined with the aforementioned encoding procedures.

In this context, the crucial encoding stage stands out, commencing with the preparation of a quantum dataset—this stage is the focus of the study. These data primarily originate from the classical processing of vibration signals, involving the extraction of features from these signals. This stage encompasses the selection and organization of this input data into a format suitable for quantum processing. Additionally, with the prepared dataset, the model is trained to learn relevant patterns and features. The evaluation of the quantum model typically involves the use of a Parameterized Quantum Circuit (PQC), a key component in the representation and manipulation of quantum data and information. From this perspective, in this work, two PQC configurations were used along with encoding methods: "Ry, Rz, Ry + CZ" and "Ry, Rz, Ry + iSWAP". After training, the system enters the sampling phase, during which information or results are extracted from the generated quantum states. Finally, the classical model evaluation procedure is performed, fundamental for establishing a basis for comparison between classical and quantum methods.

This parapgraph presents the main results obtained from the application of Angle, Amplitude and ZFeaturemap encoding. The use of Angle Encoding showed that QML models that use eight features presented the best accuracy, reaching 93.81%. This approach demonstrated superior performance compared to models that used 14 features. Furthermore, the PQC of rotation gates Ry, Rz, and the CZ gate stood out as the most effective in this context.

In the case of Amplitude Encoding, QML models with ten features, combined with the zero-padding procedure (re-dimensioning the number of features to 16), showed the best accuracy (92.71%). However, these results were slightly lower than those achieved by Angle Encoding. The specific configuration of PQC with CZ and iSWAP was identified as the most efficient in this encoding method.

For the ZFeaturemap method, the QML models that used five features showed the best accuracies, reaching 95.74% and 95.02%. These results were superior compared to Angle Encoding, regardless of the number of features used. This encoding method proved to be particularly effective for more compact representations of data.

The present study was designed with the central objective of investigating different encoding structures in the context of QML. By testing the Angle Encoding, Amplitude Encoding, ZFeaturemap and ZZFeaturemap approaches, we seek to understand how these structures influence the performance of quantum models in specific tasks, with a focus on bearing vibration analysis. The results obtained revealed significant nuances between the encoding methods. One can observe that, although there are currently limitations regarding the use of the quantum methods, the results obtained with quantum coding methods surpassed the performance of classical ML models. Zfeaturemap proved to be particularly effective for compact representations of data, while Angle Encoding and Amplitude Encoding demonstrated their advantages in specific contexts, using 10 and 14 features as input data. Furthermore, it is crucial to recognize the limitations of this research. The use of quantum simulators may influence results as actual quantum behavior may differ. Furthermore, the structures tested were specific to the context of bearing vibration analysis and may not be generalizable to other applications.


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