International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 2259-2263 www.ijaem.net ISSN: 2395-5252

An Efficient Model for the Reduction of Complexity in Fuzzy Systems

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Submitted: 20-05-2022 Revised: 28-05-2022 Accepted: 30-05-2022

ABSTRACT-Complexity has been a major challenge in building systems using fuzzy sets. Complexity in fuzzy systems happens as a result of the increase in the number of input features, the computation time, and the memory space taken by the fuzzy systems to complete execution. The problem of complexity in fuzzy systems has caused a reduction in performance of the systems in terms of giving accurate results (The number of false-positive, negative, true positive, and negative.)., This paper presents a complexity reduction technique for fuzzy systems. The technique adopted Principal Component Analysis (PCA)approach. As the number of features increased, PCA was used in reducing the computational complexity (time and space) in a fuzzy system by extracting the important features in the input data without losing the original quality of the data. The extracted features from the PCA were applied to a fuzzy system in reducing the computational complexity and thereby increasing the performance of the fuzzy system. The results of the PCA were compared to other existing methods, and the PCA gave a lesser computational time and memory usage than other existing methods.
Keywords: Fuzzy System, Complexity Reduction, Principal Component Analysis, Neuro-Fuzzy

I. INTRODUCTION

The concept of fuzzy logic seems to be an outstanding method to address the synthesis of complex nonlinear structures in the previous century. Due to their conceptual simplicity, fuzzy schemes primarily based totally on Takagi Sugeno (T-S) fuzzy models have become the maximum famous and convenient. The general model of the system is produced in T-S fuzzy fashions through fuzzy "blending" of nearby linear models, the usage of membership functions, which might also additionally then take complete advantage of modern manage gear like Linear Matrix Inequality (LMI) approach. As a result, the last decade has seen a plethora of research efforts on T-S fuzzy systems, with numerous successful consequences mentioned in various areas which include stability analysis and stabilization filter design, observability, and so on [1]

The fundamental ideas of fuzzy rule bases are used to control complexity in fuzzy systems. These residences mirror the range of variations of linguistic values of inputs and outputs which are available, as well as the sort of mapping that exists among the variations of linguistic values of inputs in the antecedent part of the rule-base and the corresponding diversifications of linguistic values of outputs in the next part. Although current technological improvements have made our lives less difficult in lots of ways, they've additionally added new problems which have brought to the international's general complexity [2].

Soft computing strategies for modeling, prediction, and manipulating programs of dynamic nonlinear structures have been evolved in reaction to issues related to computational speed, accuracy, and layout of complexity. Soft computation strategies which include Artificial Neural Networks (ANN) and Fuzzy Logic structures are extensively used. Fusion of these two methodologies is being used to solve real-world challenges in a variety of scientific and engineering domains. Fuzzy logic can directly improve a learning machine's thinking and inference. The qualitative, albeit imprecise, knowledge may be described to allow machine learning to be expressed symbolically using fuzzy logic. The use of neural networks presents the system with mastering capabilities, robustness, and massive parallelism. The neuro-fuzzy system's knowledge representation and automated learning capabilities make it a formidable framework for issues with machine learning [3].

Because most jobs are time-critical, they must be completed with a guaranteed response time using restricted resources. Furthermore, the quantity of available time and resources can vary depending on the conditions, and processing time resource constraints can emerge at any time. In these situations, so-called anytime techniques can be utilized to avert significant performance failures by providing quick response times and flexibility in terms of available time and resources [4]

Fuzzy and neural systems, on the other hand, can be useful even when the problem is too difficult to answer with traditional methods, because they do not require a perfect mathematical description, simply expert knowledge and/or sample data. However, the usability of fuzzy and neural tools in timocratical or anytime applications is constrained by their exponentially increasing complexity, which is compounded by the lack of approach for specifying the system's complexity needs. Higher complexity, as measured by the number of antecedent fuzzy sets or nodes, usually translates to a better approximation of the original system.

II. RELATED LITERATURE

[5]Presented a hybrid Neuro-Fuzzy and Feature Reduction (NF-FR) model. For all of the patterns, the proposed NF-FR model employs a feature-based class belongingness fuzzification approach. All features are extended during the fuzzification process are dependent on the number of classes available in the dataset. It aids the Artificial Neural Network (ANN)-based model in achieving higher performance by addressing uncertainty issues. The NF-FR model has a significant improvement in accuracy and is proven to be efficient in reducing redundant and noisy information, according to their experimental results, analysis, and statistical analysis.

[6]Created a hybrid intelligent system that combines three algorithms. They used Linear Discriminant Analysis (LDA) to reduce complexity, Support Vector Machines (SVM) to classify, and Genetic Algorithms (GA) to optimize SVMs. As a result, the three models are combined into a single black-box model called LDA–GA–SVM.

[7]Presented Hierarchical Fuzzy Systems (HFS) as a solution to the dimensionality curse, which is the most significant problem of using fuzzy models in the modeling and control of large-scale systems. Time series prediction and function approximation are used to assess the performance of the hierarchical fuzzy system, demonstrating that the proposed HFS, when combined with genetic algorithm (GA) parameter optimization and k-means clustering in the fuzzy partition, produces structurally simple and accurate fuzzy models.

[8] Used Akagi-Sugeno kind fuzzy approximation to sieve out the irrelevant records in the rule-base to minimize the various sets of the antecedent, as a result, the variety of rules. This proposed technique is a non-linear extension of the lately posted fuzzy approximation method primarily based totally on singular value decomposition which makes use of individual support.

[9]Introduces fuzzy-optimized statistics management for classifying and enhancing coalition of collected facts primarily based totally on semantics and constraints. This method segregates the attributes primarily based totally on similarity index limitations to system complicated statistics in a managed time. The overall performance of the proposed FDM has analyzed the use of a real-time climate forecast dataset including sensor statistics (observed) and picture statistics (captured). With this dataset, the capabilities of FDM which include entering semantics analytics and class primarily based totally on similarity are performed. The metrics class, processing time and correspondence index are analyzed for the various statistics sizes, class instances, and dataset records. The proposed FDM is known to acquire 36.28% much less processing time for various class instances, and 12.57% excessive similarity index.

[10]Presented a reduction technique withrigorous selection and deselection features that are entered as input. The pENsemble acquires a rigorous ensemble shape to output a very last class choice in which it features a singular glide detection state of affairs to develop the ensemble's shape. The efficacy of the pENsemble has been numerically established via dynamic numerical research with rigorous and evolving facts streams in which it gives you the maximum encouraging overall performance in achieving a tradeoff among accuracy and complexity.

[11]Minimized the computational complexity by using a rigorous surface control approach. A real tolerant of fault control approach was built to practically stable the fuzzy system and also converge the error acquired during tracking to a small residuary set in a finite time.

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III. SYSTEM DESIGN

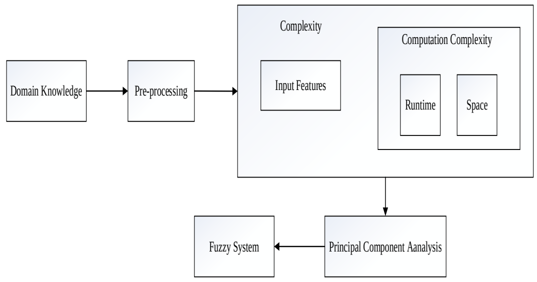

Figure 1: System Architecture

The System is composed of the following components:

Domain Knowledge: The domain knowledge is a statement expression relating to all facts that define the constrains and problem (the limitations being a part of the problem). Here, the problem area is to pick out and decrease the elements that create complexity by the use of Principal Component Analysis.

Pre-Processing: The data pre-processing that will be carried out by checking and removal of Nan values, and data scaling. Data scaling is an essential pre-processing step. Data scaling may be accomplished through normalizing or standardizing real-valued entries and output variables. Therefore, for information scaling, MinMaxScaler feature is utilized in subtracting the minimal characteristic after which it divides through the variety. The variety is the distinction among the authentic most and authentic minimal of the dataset.

Complexity: The complexity in a fuzzy system is caused by the following factors:

i. **Input Features:** In a few domains problem, the data entered will increase from X_1 to X_n wherein X is the entered data, and **n** is the wide variety of capabilities. However, the complexity of the problem will increase because of this enlargement of entered data within the fuzzification process. This is due to the fact that the wide variety of data entered will increase, which results in the expansion or increase of the fuzzy rules.

ii. **Computational Complexity:** The computational complexity is a degree of the number of computing resources (time and space) that a fuzzy device consumes whilst it runs. A little description of the time and space can be seen below:

a. **Runtime:** Another element that results in complexity in a fuzzy system is the runtime. By runtime, we imply how long does the system take in finishing a selected task. Therefore, complexity in fuzzy systems reasons the system to spend greater time running earlier than finishing its execution.

b. **Space:** The space has to do with the memory space the fuzzy system consumes in carrying out a particular task.

Fuzzy System: The Fuzzy Logic behavesthe logic of humans and Artificial Neural networks. It has a minimum system time than different methods with more correct results. The fuzzy System relies upon gaining knowledge of a set of rules with converting policies and /or features to observe input/output training data. The preliminary structure of the network calls for picking the range of policies, which relies upon the community's pre-recognized data. Measurements of the machine might be used to decide the variety of policies range (most and minimum).

Principal Component Analysis: Due to the problems of complexity in fuzzy system, Principal Component Analysis (PCA) approach could be utilized in lowering the complexities in a fuzzy system because the dataset capabilities expand from factor $\mathbf{i_1}$to $\mathbf{i_n}$, wherein **i**represents theinput characteristics and **n**=1,2,3 Principal Component Analysis (PCA) is a matrix factorization approach that generalizes the Eigen decomposition of a rectangular matrix (**m x n**) to any matrix (**n x m**). Principal Component Analysis. PCA-primarily based totally reduce complexity algorithms, to provide the automated removal of the redundancy of the rule-base, so it could be used for specific complexity-discount. In maximum cases, Principal Component Analysis may be sufficient to make viable using the given fuzzy system in a time-important application.

Algorithm for Principal Component Analysis
Step 1: Calculate the covariance matrix for the functions in the dataset.
Step 2: Calculate the eigenvalues and eigenvectors for the covariance matrix.
Step 3: Sort eigenvalues and their corresponding eigenvectors.
Step 4: Pick okay eigenvalues and shape a matrix of eigenvectors.
Step 5: Transform unique matrix pseudocode for PCA

IV. RESULTS AND DISCUSSION

This section discusses the complexity reduction method used, how it is applied to a fuzzy system, and the outcome of the result when compared to a complex fuzzy system. For these purposes, Principal Component Analysis (PCA)

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was used in reducing the complexity and the reduced result of the principal component analysis will be applied to a fuzzy system that predicts the severity of breast masses. The process of the experiment is made up of two stages. The first phase has to do with Comparing the result of a fuzzy system when principal component analysis has not been applied to it to when principal component analysis has been applied to it. The second phase of the result is comparing the result of principal component analysis on a fuzzy system to other existing methods. In the first phase a fuzzy system that predicts the severity of breast masses was used for this experiment. The system uses a total of 5 input features and one output. Principal Component Analysis was applied to the input features so as to reduce the system complexity. The reduced input features before and after principal component analysis were applied to it can be seen in figure 2. The reduced result of the PCA was now applied to a fuzzy system. The evaluation of the fuzzy system with Principal Component Analysis in terms of accuracy and precision can be seen in figure3. A side-by-side comparison of the reduced complex fuzzy system and the non-reduced complex system can be seen in table 1.A bar chart will be used to check the performance of the fuzzy system with PCA and the fuzzy system without PCA. The bar chart representation can be seen in figure 4. After training and evaluation of model performance, the result of the proposed system for the reduction of complexity in the fuzzy system was carried out.The proposed method made used Principal Component Analysis (PCA), whereas the existing system made use of Linear Discriminant Analysis in reducing complexity in the fuzzy system. The comparison results of the existing system and the proposed system in terms of memory space. This can be seen in Tables 2, And figure 5.

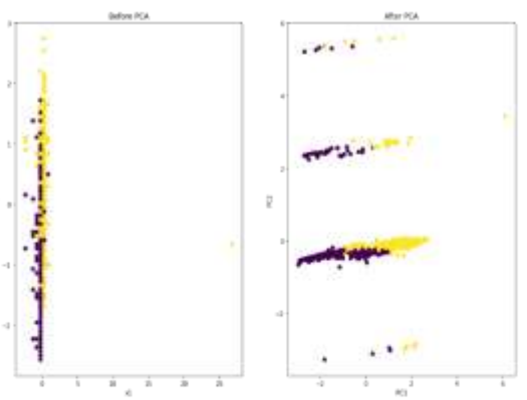

Figure 2: Result of PCA when applied to the input features

The PCA result shows that the first and third features (0, 2) are the most important features in the dataset. therefore, it can be applied in building a fuzzy system without losing the original content of the data.

Figure 3: Matrix Evaluation of the reduced Complex fuzzy system

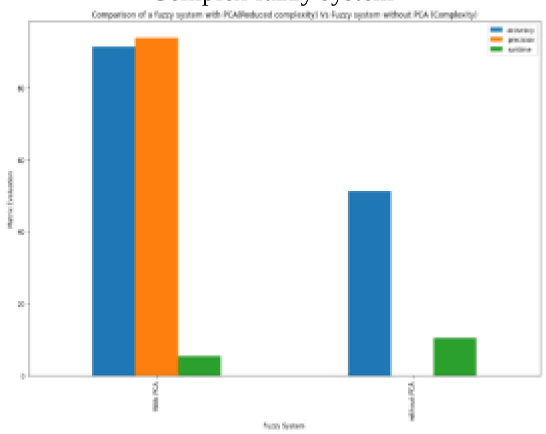

Figure 4: Comparison of a Reduced complex Fuzzy System vs a Complex Fuzzy System

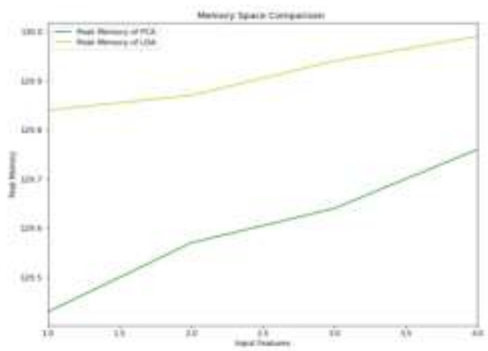

Figure 5: Comparison graph between system with PCA and the existing system in terms of complexity

V. CONCLUSION

Higher complexity - better quantity of antecedent fuzzy units or nodes - generally effects in a higher approximation of the unique system. To attain the wanted accuracy, one may be tempted to overestimate the wanted complexity. which l may lead to large and redundant structures. The flexible variation of complexity during the operation of the system is likewise a problem (Orsolya et.al., 2015).

Because of the complexity problem and fuzzy system, this paper proposed a reduction technique named principal component analysis that was used in reducing the complexity. The technique was applied to a fuzzy system for complexity reduction. The result of the principal component analysis shows how the fuzzy system runtime was reduced and a better accuracy was achieved. The achieved accuracy was 91.55%. The result of the principal component analysis was compared to an existing reduction method called Linear Discriminant Analysis (LDA). The comparison was also done in terms of accuracy, precision, and runtime. Here, a comparison was carried out between an existing method (Linear Discriminant Analysis) and the proposed technique (Principal Component Analysis). The result shows that principal component analysis outperforms linear discriminant analysis with an accuracy level of 91.55%, precision 94%, runtime 5.44secs over 90.30%, 93% and a runtime of 7.46s. Therefore, this is to say that complexity reduction in fuzzy system using principal component analysis produces a better result.

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