MUŞ ALPARSLAN ÜNİVERSİTESİ
HENDESE TEKNİK BİLİMLER VE MÜHENDİSLİK DERGİSİ
MUŞ ALPARSLAN UNIVERSITY
JOURNAL OF HENDESE TECHNICAL SCIENCES AND ENGINEERING
Muş Alparslan Üniversitesi Külliyesi Teknik Bilimler Meslek Yüksekokulu, 49250, Muş, Türkiye
https://dergipark.org.tr/en/pub/hendese/board
e-ISSN: 3023-7777
HENDESE Nisan 2026, 3 (1): 1-37
Cilt / Volume: 3 **Sayı / Issue: 1** **Yıl / Year: 2026**

Optimization of MR Image Quality Using Fuzzy Logic

Ebuzer AYGUL[1]

[1] *Vocational School of Health Services, Hakkari University, Hakkari, TÜRKİYE*
ebuzeraygul@hakkari.edu.tr—ORCID 0000-0003-0930-3975

Article Information

Article Types	Research Article
Received	24 Febraury 2026
Accepted	27 April 2026

Year: 2026 | **Volume:** 3 | **Issue:** 1 | **Pages:** 9-14

Cite as: E. Aygul, "Optimization of MR image quality using fuzzy logic," *Hendese Journal of Technical Sciences and Engineering*, Vol. 3, No. 1, pp. 9–14, 2026, doi: 10.5281/zenodo.19899918.

Corresponding Author: Ebuzer AYGUL

HENDESE TEKNİK BİLİMLER ve MÜHENDİSLİK DERGİSİ
JOURNAL of HENDESE TECHNICAL SCIENCES and ENGINEERING
RESEARCH ARTICLE

Optimization of MR Image Quality Using Fuzzy Logic

Ebuzer AYGUL[*1]

[1]*Vocational School of Health Services, Hakkari University, Hakkari, TÜRKİYE*

(**Received:** 24.02.2026, **Accepted:** 27.04.2026, **Published Online:** 30.04.2026)

Keywords
MR,
Image Quality,
Fuzzy Logic

ABSTRACT

Magnetic resonance image quality is a complex process involving multiple acquisition parameters such as the image matrix, number of excitations (NEX), field of view (FOV), and signal-to-noise ratio (SNR). The nonlinear relationships among these parameters can lead to unwanted artifacts in the images and negatively affect critical factors in healthcare, such as speed and accuracy. Therefore, improving MR image quality is expected to be more effectively achieved by combining these nonlinear parameters with artificial intelligence techniques, specifically fuzzy logic, rather than relying solely on traditional mathematical optimization methods, allowing for a more flexible and robust relational model. As a result of the fuzzy logic model developed for MRI image quality optimization, it has been demonstrated that fuzzy logic is an effective method for modeling nonlinear parameters. Accordingly, it has been revealed that high SNR and large matrix values among the input parameters play a direct role in image quality.

Published by Muş Alparslan University, Muş, Türkiye

***Corresponding Author:** ebuzeraygul@hakkari.edu.tr

Volume: 3 **Issue:** 1

Cite as: E. Aygul, "Optimization of MR image quality using fuzzy logic," *Hendese Journal of Technical Sciences and Engineering*, Vol. 3, No. 1, pp. 9–14, 2026, doi: 10.5281/zenodo.19899918.

Doi: 10.5281/zenodo.19899918

1. INTRODUCTION

Magnetic Resonance Imaging (MRI) has evolved significantly since the early discoveries of nuclear magnetic resonance (NMR) in 1946 and the first images produced in 1973. While early systems operated at lower magnetic fields, modern clinical practice now utilizes 1.5T, 3T, and even 7T systems for advanced research. Despite these technological leaps, image quality remains sensitive to various acquisition parameters, such as the image matrix, number of excitations (NEX), field of view (FOV), and signal-to-noise ratio (SNR) [1-3]. The relationship between these parameters is inherently nonlinear. For instance, increasing the matrix size improves resolution but can decrease the SNR, while increasing NEX improves SNR at the cost of prolonged scan times. Recent literature (2023-2025) suggests that artificial intelligence and fuzzy logic are increasingly vital for managing these uncertainties without requiring explicit, rigid mathematical models. This study employs a Mamdani-type fuzzy system to balance these conflicting parameters and optimize diagnostic image quality [4]. By 1973, the magnetic resonance technique had become a phenomenon when Paul Lauterbur successfully produced the first MR image using gradient fields. By the 1980s, MR had begun to replace tomography devices in clinical practice, as it provided more effective results in soft tissue and cancer imaging. MR quickly became established as the first medical imaging device of its kind in hospitals, particularly for imaging the brain and spinal cord. It was accepted as a radiation-free alternative to computed tomography (CT) in clinical applications [5], [6].

Between 1990 and 2000, 1.5 Tesla MR systems became standard. In later years, 3 Tesla MR devices began to be used in clinical practice, alongside the development of new techniques, such as diffusion MR imaging (DWI), perfusion MR, MR angiography (MRA), and functional MR imaging (fMRI) [7], [8]. Modern MR technology (2010–2020+) features widespread 3T systems and 7T devices for research and advanced clinical use. Artificial intelligence–assisted image reconstruction, faster sequences, and shorter scan times have been introduced, leading to advanced applications in clinical fields such as cardiac MR and oncological imaging [9].

The MRI system is a highly functional and important tool for clinical support applications. Despite all its clinical advantages, image distortions can occur due to physical principles, patient movement, sequence characteristics, and hardware issues. In MR imaging, these image distortions are referred to as artifacts. The main factors influencing artifacts in MR applications, which are also interrelated to varying degrees, can be categorized as the image matrix, number of excitations (NEX), field of view (FOV), and signal-to-noise ratio (SNR) [10], [11].

Matrix: This parameter determines the pixel values on the image display. A larger matrix (e.g., 256 × 256 or 192 × 256) results in smaller pixels forming the image, thereby improving image quality [12].

NEX (Number of Excitations): NEX averages the phase-encoding steps to generate the image. It directly affects the signal-to-noise ratio (SNR), and thus influences overall image quality [13].

FOV (Field of View): FOV directly affects the SNR and determines the size of the tissue displayed on the screen. Its unit of measurement is centimeters (cm) [14].

SNR (Signal-to-Noise Ratio): This value represents the ratio of signal to noise and directly impacts image quality depending on whether the noise level is high or low. Matrix size, FOV, NEX, and spatial resolution all directly influence the SNR [15].

The mathematical relationship among these parameters is:

$$\text{SNR} = \text{voxel volume} \times \sqrt{NEX}$$

$$\text{Pixel} = {}^{FOV}\!/_{Matrix}$$

as expressed,

The nonlinear relationships among these parameters can be modeled using a fuzzy logic–based network, offering a more flexible strategy for optimization [16], [17]. Fuzzy logic is an artificial intelligence technique capable of managing nonlinear systems without requiring explicit mathematical models, relying instead on expert knowledge and rules. It also provides flexible and rapid prototyping capabilities. This approach can be applied to develop a model that enhances MR image quality, enabling a fuzzy logic–based MR quality model to handle uncertainty and nonlinear interactions among matrix, FOV, NEX, and SNR, while making human-like flexible decisions for image optimization.

2. MATERIAL AND METHOD

In this study, fuzzy logic, one of the artificial intelligence techniques, was used for MRI image quality optimization. For the optimization model, the Fuzzy Logic Designer Toolbox of MATLAB R2025b engineering and simulation software was utilized. Four primary input variables were defined based on their clinical impact on artifacts and resolution: SNR, Matrix, FOV, and NEX. The input values were determined from the literature, and the nonlinear relationships among these values were the driving factor in selecting fuzzy logic.

Fuzzy logic, developed by Lotfi A. Zadeh in 1965, is a long-standing logical theory that, in contrast to the uncertain and precise values of classical logic, assigns and focuses specific degrees to objects [18]. This feature is represented as a mathematical model closer to the mathematical model of thinking, assigning partial values instead of precise values to objects that are closer to the human thought unit. This feature has been widely used in many engineering fields, particularly artificial intelligence, from the past to the present. Today, it maintains its importance as an effective method, especially in solving nonlinear and uncertain problems, and is expected to become even more widespread in smart systems and hybrid artificial intelligence applications in the future [19].

For MR image quality optimization, a fuzzy logic model was developed using the MATLAB Fuzzy Logic Designer Toolbox.

In the created fuzzy logic model, the inputs are SNR, Matrix, FOV, and NEX, which have nonlinear relationships among them. The membership functions for these inputs are shown in Fig. 1 membership function of SNR, Fig. 2 membership function of matrix, Fig. 3 membership function of FOV, Fig. 4 membership function of NEX and Fig. 5 image quality of membership function. The output is the image quality score (ranging from 0 to 100 for sampling purposes).

2.1. Fuzzification and Membership Functions

In this study, triangular membership functions were selected for both input and output variables. While Gaussian functions offer smoothness, triangular MFs were chosen due to their computational efficiency and linear transition characteristics, which align well with how technicians manually adjust MRI parameters in discrete steps. They provide a clear "overlap" area that effectively models the transition between, for example, a "Medium" and "High" SNR without unnecessary mathematical complexity.

For each input, three linguistic variables (Low, Medium, High) were assigned using triangular membership functions.

- **SNR:** Ranges from 0 to 100, representing the relative signal strength.
- **Matrix:** Defined from 128 to 320 to reflect standard clinical resolutions.
- **FOV:** Ranges from 10 cm to 30 cm.
- **NEX:** Ranges from 1 to 4.

The output, Image Quality, is represented on a scale of 0 to 100. A score of 80–100 corresponds to "Very High" diagnostic quality, while scores below 40 indicate "Low" quality with significant artifacts.

2.2. Rule Base and Defuzzification

The system operates on 81 rules (3^4) derived from expert radiological knowledge. The inference process follows four stages:

1. **Fuzzification:** Numerical inputs are converted into fuzzy values.
2. **Rule Evaluation:** The Min operator is used for rule activation.
3. **Aggregation:** Rule outputs are combined using the Max operator.
4. **Defuzzification:** The **Centroid method** was selected to calculate the center of gravity of the final fuzzy set, providing a single crisp numerical quality score.

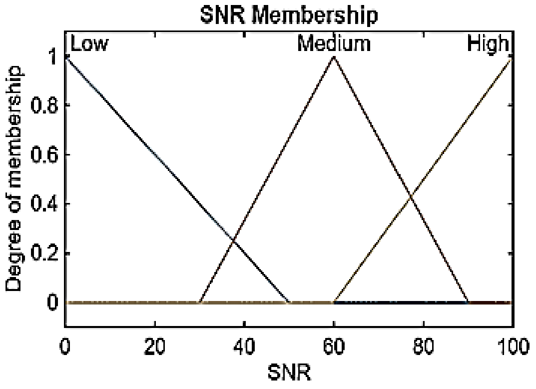

Fig. 1. Membership function of SNR.

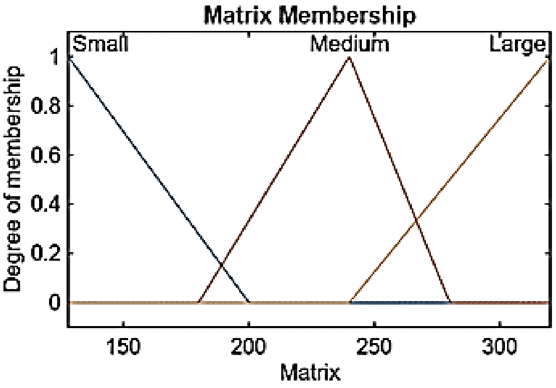

Fig. 2. Membership function of matrix.

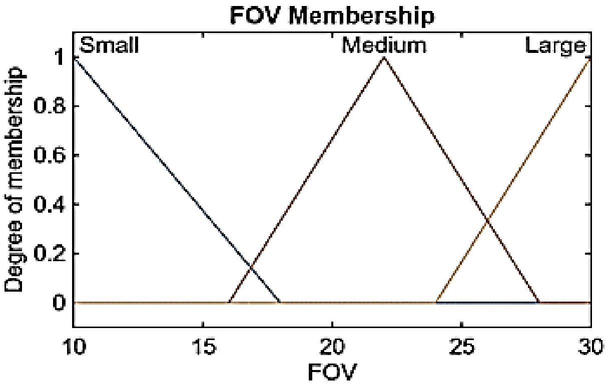

Fig. 3. Membership function of FOV.

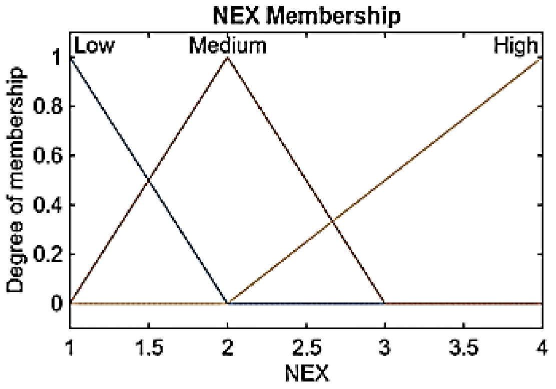

Fig. 4. Membership function of NEX.

In classical logic, when examining input values according to fixed rules: if SNR is high, image quality is high; if the matrix is large, resolution increases but SNR may decrease; if FOV is small, resolution improves but SNR decreases; and if NEX increases, SNR improves but scan time is prolonged. These relationships are nonlinear, making them suitable for fuzzy logic applications. For each input, membership functions have been defined with three linguistic variables.

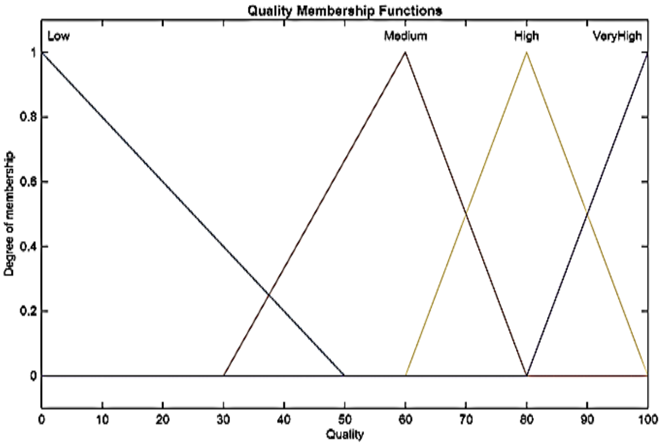

Fig. 5. Membership function of image quality.

For each membership function, a triangular function was selected. The membership function values were established based on current data, and the fuzzification process was carried out according to expert opinion. The model rules were created by defining 4 input variables, each with 3 membership functions, resulting in 3×3×3×3=81 rules. The fundamental rules, derived from expert knowledge, are presented below, and a summary of the rule table is shown in Table I.

- IF SNR is High AND Matrix is Large THEN Quality is Very High
- IF SNR is Low THEN Quality is Low
- IF Matrix is Large AND FOV is Small THEN Resolution is High
- IF FOV is Small AND SNR is Low THEN Quality is Medium
- IF NEX is High THEN SNR improves
- IF NEX is Low AND Matrix is Large THEN Quality is Medium-Low
- IF SNR is Medium AND Matrix is Medium AND FOV is Medium THEN Quality is High
- IF FOV is Large AND Matrix is Small THEN Quality is Medium

Table I. Rule table of fuzzy logic model.

SNR	Matrix	FOV	NEX	Quality
Low	Any	Any	Any	Low
Medium	Medium	Medium	Medium	High
High	Large	Small	Medium	Very High
Medium	Large	Small	Low	Medium
High	Small	Large	Low	Medium
High	Large	Medium	High	Excellent

3. RESULT AND DISCUSSION

The model successfully balanced the conflicting relationships between acquisition parameters. Surface result graphs (Fig. (6-8)) demonstrate that image quality does not increase linearly with a single parameter; rather, it requires a synchronized optimization of SNR and Matrix size. A Mamdani-type fuzzy system was used for the optimization of the MRI image quality model created using fuzzy logic. The Mamdani-type fuzzy system basically consists of four steps, which are listed respectively in Table II.

Table II. Working principle of a fuzzy logic model.

Order	Step	Description
1	Fuzzification	Numerical inputs are converted into fuzzy values using membership functions.
2	Rule Evaluation	The rules are applied; the rule activation degree is calculated using the min operator.
3	Aggregation	All rule outputs are combined using the max operator.
4	Defuzzification	The fuzzy outputs are converted into a single numerical value using the centroid method.

It was observed that the conflicting relationship disorder among the nonlinear parameters was balanced at the end of the model. Accordingly, when the result graphs provided by the model are examined, Fig. (6-9) shows that an increase in SNR does not linearly increase image quality; however, high SNR and a large matrix value yield the highest image quality Fig. 6. In Fig. 7, image quality balance can be achieved with a small FOV and high resolution but low SNR. Although increasing the Matrix and NEX values appears to be directly proportional, this relationship shows an inverse proportionality with respect to NEX. When all optimum values are considered, the effective pressure of the SNR input value is clearly evident given the Fig. 9.

3.1. Quantitative Observations

- **High Quality Thresholds:** The highest quality scores (Excellent) were achieved when a high SNR was coupled with a large matrix and medium-to-high NEX.
- **Parameter Pressure:** As shown in Fig. 9, the SNR input exerts the most significant effective pressure on the final quality score, confirming that without a baseline signal level, resolution adjustments (Matrix/FOV) cannot compensate for image degradation.

3.2. Limitations

While the fuzzy logic model provides a flexible framework, its current iteration relies on a simplified 81-rule base. In complex clinical scenarios involving patient motion or specific hardware limitations, a larger number of linguistic variables ("Low" or "Very High") might be required to capture finer nuances in image distortion.

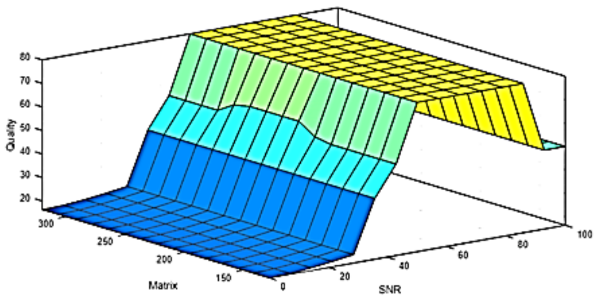

Fig. 6. Surface result graph of matrix and SNR.

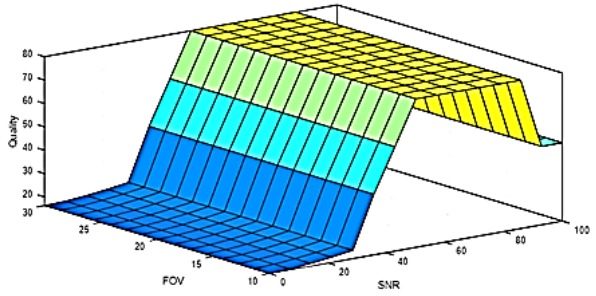

Fig. 7. Surface result graph of FOV and SNR.

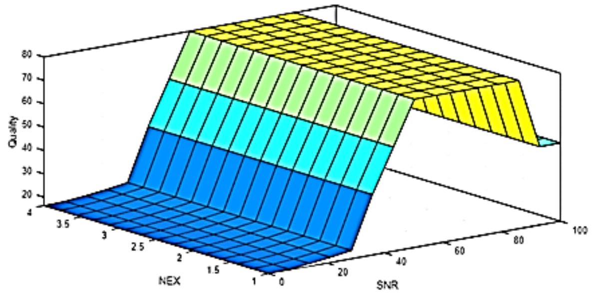

Fig. 8. Surface result graph of NEX and SNR.

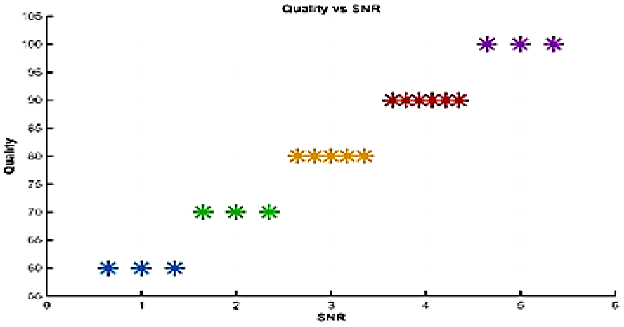

Fig. 9. Optimal image quality graph as a function of SNR.

4. CONCLUSIONS

This study demonstrates that fuzzy logic is a robust method for modeling the nonlinear and uncertain parameters of MRI acquisition. By integrating expert knowledge into the Mamdani system, we successfully optimized image quality scores, identifying high SNR and large matrix values as the primary drivers of diagnostic excellence.

Upon examining the developed model, it was observed that fuzzy logic is an appropriate choice for handling nonlinear parameters. In clinical practice, both MR devices and their derivatives, as essential diagnostic and support tools, can be made more functional through artificial intelligence–based applications. In this study, the MR fuzzy logic model successfully optimized image quality. Among the factors directly affecting image quality—matrix, FOV, NEX, and SNR—it was determined that high SNR and a large matrix yielded the highest-quality images.

Future Work: Future iterations of this model should integrate Neuro-Fuzzy (ANFIS) systems to allow the key-rule base to "learn" and adapt from real-world MRI datasets, further bridging the gap between theoretical modeling and clinical application.

ACKNOWLEDGEMENTS

Artificial intelligence software was utilized to enhance the fluency and academic quality of the manuscript.

REFERENCES

[1] H. Semat and J. R. Albright, *Introduction to Atomic and Nuclear Physics*, 5th ed. New York, NY, USA: Springer, 2012, doi: 10.1007/978-1-4615-9701-8.

[2] M. R. Madiyeva, D. T. Raissov, A. G. Kuanysheva, A. V. Rakhimbekov, M. N. Baizakova, and K. A. Tussupzhanova, “History and development prospects of magnetic resonance imaging,” *Nauka i Zdravookhranenie*, Vol. 20, No. 6, pp. 169–175, 2018.

[3] J. M. Wardlaw et al., “A systematic review of the utility of 1.5 versus 3 Tesla magnetic resonance brain imaging in clinical practice and research,” *European Radiology*, Vol. 22, No. 11, pp. 2295–2303, 2012, doi: 10.1007/s00330-012-2500-8.

[4] M. K. Jha, “Handling uncertain information with fuzzy logic in locating new infrastructure,” *Journal of Data Science and Intelligent Systems*, pp. 1–10, 2025, doi: 10.47852/bonviewJDSIS52025076.

[5] N. R. Jagannathan, “Potential of magnetic resonance (MR) methods in clinical cancer research,” in *Biomedical Translational Research: Technologies for Improving Healthcare*. Singapore: Springer Nature Singapore, 2022, pp. 339–360, doi: 10.1007/978-981-16-4345-3_21.

[6] H. Kabasawa, “MR imaging in the 21st century: Technical innovation over the first two decades,” *Magnetic Resonance in Medical Sciences*, Vol. 21, No. 1, pp. 71–82, 2022, doi: 10.2463/mrms.rev.2021-0011.

[7] H. Yang et al., “Artificial intelligence for neuro MRI acquisition: A review,” *Magnetic Resonance Materials in Physics, Biology and Medicine*, Vol. 37, No. 3, pp. 383–396, 2024, doi: 10.1007/s10334-024-01182-7.

[8] D. S. Lakomy et al., “Clinical implementation and initial experience with a 1.5 Tesla MR-Linac for MR-guided radiation therapy for gynecologic cancer: An R-IDEAL stage 1 and 2a first in humans feasibility study of new technology implementation,” *Practical Radiation Oncology*, Vol. 12, No. 4, pp. e296–e305, 2022, doi: 10.1016/j.prro.2022.03.002.

[9] F. A. Cardillo, F. Masulli, and S. Rovetta, “Automatic approaches for CE-MRI examination of the breast: A survey,” in *Proc. 2017 IEEE Int. Conf. Internet of Things (iThings), IEEE Green*

Computing and Communications (GreenCom), IEEE Cyber, Physical and Social Computing (CPSCom), and IEEE Smart Data (SmartData), Exeter, UK, 2017, pp. 147–154, doi: 10.1109/iThings-GreenCom-CPSCom-SmartData.2017.27.

[10] Y.-C. Heo, H.-K. Lee, and J.-H. Cho, "Effects of NEX on SNR and artifacts in parallel MR images acquired using reference scan," *Journal of Magnetics*, Vol. 18, No. 4, pp. 422–427, 2013, doi: 10.4283/JMAG.2013.18.4.422.

[11] M. W. Haskell, J.-F. Nielsen, and D. C. Noll, "Off-resonance artifact correction for MRI: A review," *NMR in Biomedicine*, Vol. 36, No. 5, Art. no. e4867, 2023, doi: 10.1002/nbm.4867.

[12] S. Thukral and J. S. Bal, "Medical applications on fuzzy logic inference system: A review," *International Journal of Advanced Networking and Applications*, Vol. 10, No. 4, pp. 3944–3950, 2019.

[13] S.-J. Yoo, H.-Y. Yang, and S.-H. Kim, "Comparison of image quality according to reduction of scan time in MRI: Change in acceleration factor of parallel imaging and NEX," *Journal of the Korean Society of Radiology*, Vol. 18, No. 7, pp. 903–910, 2024, doi: 10.7742/jksr.2024.18.7.903.

[14] M. Teimoorisichani, V. Panin, H. Rothfuss, H. Sari, A. Rominger, and M. Conti, "A CT-less approach to quantitative PET imaging using the LSO intrinsic radiation for long-axial FOV PET scanners," *Medical Physics*, Vol. 49, No. 1, pp. 309–323, 2022, doi: 10.1002/mp.15376.

[15] R. Ayde, M. Vornehm, Y. Zhao, F. Knoll, E. X. Wu, and M. Sarracanie, "MRI at low field: A review of software solutions for improving SNR," *NMR in Biomedicine*, Vol. 38, No. 1, Art. no. e5268, 2025, doi: 10.1002/nbm.5268.

[16] H. R. Patel and V. A. Shah, "Fuzzy logic-based metaheuristic algorithm for optimization of type-1 fuzzy controller: Fault-tolerant control for nonlinear system with actuator fault," *IFAC-PapersOnLine*, Vol. 55, No. 1, pp. 715–721, 2022, doi: 10.1016/j.ifacol.2022.04.117.

[17] P. Pei, S. T. Quek, and Y. Peng, "Multiobjective reliability-based design optimization of the fuzzy logic controller for MR damper-based structures," *Structural Control and Health Monitoring*, Vol. 2023, Art. no. 4009397, 2023, doi: 10.1155/2023/4009397.

[18] L. A. Zadeh, "Fuzzy logic," in *Granular, Fuzzy, and Soft Computing*. New York, NY, USA: Springer, 2023, pp. 19–49, doi: 10.1007/978-1-0716-2628-3_234.

[19] I. Melnyk, S. Tuhai, M. Skrypka, and I. Shved, "Fuzzy logic models for technological and communication electronic control systems," in *Digital Ecosystems: Interconnecting Advanced Networks with AI Applications*. Cham, Switzerland: Springer Nature Switzerland, 2024, pp. 337–363, doi: 10.1007/978-3-031-61221-3_17.