2025 Volume: 01 Issue: 07 www.ijrpa.com ISSN 2456-9995

Research Article

International Journal Research Publication Analysis

Page: 01-09

A STUDY COMPARING HADAMARD TRANSFORM-BASED METHODS FOR REINFORCEMENT LEARNING IN X-RAY IMAGING

Rashia Subashree R*[1], Dr. Nancy Jasmine Goldena[2]

[1]Research Scholar, Reg.no: 23211202282006, Department of Computer Application and Research Centre, Sarah Tucker College (Autonomous), Affiliated to Manonmaniam Sundaranar University, Tirunelveli - 627007.

[2]Associate Professor, Department of Computer Application and Research Centre, Sarah Tucker College (Autonomous), Affiliated to Manonmaniam Sundaranar University, Tirunelveli - 627007.

Article Received: 26 October 2025

Article Revised: 14 November 2025

Published on: 05 December 2025

***Corresponding Author: Rashia Subashree R**

Research Scholar, Reg.no: 23211202282006, Department of Computer Application and Research Centre, Sarah Tucker College (Autonomous), Affiliated to Manonmaniam Sundaranar University, Tirunelveli - 627007.

DOI: https://doi-doi.org/101555/ijrpa.6413

ABSTRACT

Medical image processing is increasingly using Hadamard Transform (HT) algorithms because of their efficacy in noise reduction and feature extraction. In this work, four HT methods—Standard HT, Fractional HT, Fast HT, and Adaptive HT—are evaluated for X-ray image processing using a Deep Q-Network (DQN)-based reinforcement learning (RL) framework. By preprocessing X-ray pictures, the HT approaches convert features into learning-optimized domains. Fractional HT performs the best overall, according to the results, and is especially good at identifying minute irregularities in noisy pictures since it excels at feature extraction and noise resistance. Despite being computationally less efficient, adaptive HT's dynamic parameter tweaking allows it to be versatile across a variety of datasets. The most computationally efficient method is Fast HT, which is appropriate for real-time applications but has a limited level of noise resistance. Standard HT is a trustworthy baseline that offers balanced performance. The results imply that the HT technique selection should be in line with the demands of the work, including computing efficiency or picture noise levels. The promise of HT in improving RL-based medical imaging processes is

highlighted by this comparative analysis, which also draws attention to the trade-offs between various HT approaches.

KEYWORDS: Hadamard Transform, Reinforcement Learning, X-ray Image Analysis, Feature Extraction, Noise Resistance.

1. INTRODUCTION

Medical imaging is essential for patient monitoring, therapy planning, and illness diagnosis. Owing to its affordability and capacity to offer comprehensive insights into interior structures, X-ray imaging is one of the most commonly used modalities. Advanced computer techniques are necessary to increase the accuracy of analysis, nevertheless, due to issues including noise, low contrast, and minute irregularities in X-ray pictures [1,2]. One machine learning model that focusses on sequential decision-making, reinforcement learning (RL), has demonstrated potential in automating challenging medical imaging tasks. For tasks like anomaly detection and picture segmentation, RL agents are ideal because they learn the best rules via interaction with their surroundings [1]. Their effectiveness is, however, highly dependent on how well the feature representations obtained from the input photos are constructed. A mathematical method called the Hadamard Transform (HT) converts data into a domain that is best suited for feature extraction. Different trade-offs in computational efficiency, feature enhancement, and noise resistance are offered by its variations, which include Standard HT, Fractional HT, Fast HT, and Adaptive HT. By offering reliable and effective feature representations, incorporating these HT approaches into RL frameworks may enhance agent performance [5]. The performance of several HT approaches in reinforcement learning for X-ray image processing is compared in this research. The study sheds light on the advantages and disadvantages of each strategy by assessing measures including computing efficiency, feature extraction, noise resistance, and RL agent performance [6]. The results are intended to improve accuracy and computing efficiency in clinical applications by directing the choice of suitable HT approaches for particular medical imaging workloads.

2. Background

2.1 Hadamard Transform (HT)

Using the Hadamard matrix, the HT is a linear orthogonal transform that is renowned for its quick computing. The transform is modified for certain uses, such as image compression and denoising, via HT variants such fractional HT and fast HT[1].

2.2 Reinforcement Learning (RL)

RL is the process of teaching agents to interact with their surroundings in order to make successive judgements [4]. RL can work on modified feature areas when combined with HT, which might improve learning effectiveness and performance.

2.3 X-Ray Image Analysis

X-ray pictures are essential for identifying cancer, infections, and fractures. For increased diagnostic accuracy, image processing methods that improve feature visibility and lower noise are essential.

3. Methodology

This study assesses how well four distinct Hadamard Transform (HT) methods operate when combined with an RL framework for X-ray picture processing. Data collection, HT-based picture preprocessing, RL agent training, and performance evaluation of several metrics comprise the methodology. A thorough explanation of the process is provided below:

3.1. Dataset

The NIH Chest X-rays and MURA (Musculoskeletal Radiographs) databases are two publicly accessible X-ray datasets that are used in this investigation. These datasets include a large range of X-ray pictures, both normal and aberrant, which are used to assess how well various HT approaches work in diverse medical situations [5].

3.2. Preprocessing with Hadamard Transform

The preprocessing step is converting the raw X-ray pictures into feature-rich representations appropriate for RL by using the four HT approaches. The HT methods that are used include:

- **Standard HT**: The basic Hadamard Transform is applied directly to the image in its standard form, without incorporating any additional modifications or enhancements.
- **Fractional HT**: A variation that enables a tuneable transformation, in which particular aspects of the picture are enhanced by fractionalising the transformation matrix.
- **Fast HT**: The standard HT has been optimised for computational efficiency. To complete the change more rapidly, it makes use of fast algorithms.
- **Adaptive HT**: A dynamic version that enhances feature extraction and noise resistance by modifying the transformation according to the unique properties of the image.

  The pixel values of the converted images are then standardised throughout the dataset by normalising them.

3.3. Reinforcement Learning Setup

Agents are trained using a Deep Q-Network (DQN)-based reinforcement learning framework to carry out tasks like X-ray picture anomaly detection and categorisation. Through actions (such as identifying anomalies or categorising regions of interest), the RL agent engages with the environment (the X-ray pictures) and is rewarded according to how accurately the actions are completed.

- **State Representation:** The HT-transformed X-ray pictures serve as the RL agent's state representation.
- **Action Space:** The agent's tasks include seeing anomalies, dividing up areas, and categorising the photos as normal or abnormal.
- **Reward Function:** Accurate predictions get a greater reward, which is dependent on the agent's capacity to identify anomalies in the pictures or categorise them properly.

3.4. Evaluation Metrics

Each HT technique's performance is assessed using the following standards:

- **Computational Efficiency:** Determined by the HT application time and the RL agent's subsequent training time.
- **Feature Extraction:** Evaluated according to the calibre of features taken from the converted photos, which have an immediate effect on the RL agent's performance.
- **Noise Resistance:** Assessed by evaluating how effectively each HT methodology manages noise after testing the methods on noisy X-ray picture versions.
- **RL Agent Performance:** This is determined by the agent's convergence time during training and its accuracy in identifying and localising abnormalities.

3.5. Experimental Setup

The following experimental protocol is used for every HT technique:

- **Preprocessing:** Give the X-ray pictures the HT method.
- **RL Training:** Use the previously processed pictures as input to train the RL agent.
- **Testing:** Assess the trained agent's performance using a test collection of photos to gauge its ability to identify anomalies and classify pictures accurately.
- **Comparison:** Examine how well each HT approach performs in relation to the assessment metrics.

3.6. Statistical Analysis

Statistical techniques such as ANOVA (Analysis of Variance) are used to compare the performance of the HT methods and determine whether the differences are statistically significant. The efficacy of the RL agent under each HT approach is further assessed by calculating the average reward and convergence time. By offering a thorough assessment of several HT approaches within the framework of reinforcement learning for X-ray image analysis, this methodology seeks to determine which strategy works best for a range of medical image processing applications.

4. Results and Analysis:

The four Hadamard Transform (HT) methods—Standard HT, Fractional HT, Fast HT, and Adaptive HT—were compared using four important metrics: RL agent performance, computational efficiency, feature extraction, and noise resistance. Results are shown below for each approach across these criteria.

4.1. Computational Efficiency

- **Fast HT** emerged to be the most computationally efficient method, exhibiting the shortest training and processing durations. This results from its efficient implementation, which cuts down on the time needed to train the RL agent and apply the HT.
- **Standard HT and Fractional HT** have equal computational efficiency and require modest processing durations, with Standard HT somewhat quicker in some circumstances.
- **Adaptive HT** showed the lowest computing efficiency due to its dynamic nature, requiring additional computations for parameter tweaking.

4.2. Feature Extraction

- **Fractional HT** generated the most reliable and comprehensive features from the X-ray pictures, outperforming the other methods in this regard. This improved the RL agent's capacity to identify irregularities and classify data accurately.
- **Adaptive HT** also demonstrated outstanding feature extraction performance, gaining from its capacity to adjust to the unique characteristics of every image, resulting in improved representations.
- **Standard and Fast HT** functioned well for feature extraction, but lacked detail and flexibility compared to Fractional and Adaptive HT.

4.3. Noise Resistance

- **Adaptive and Fractional HT** demonstrated remarkable resilience to noise, managing noisy X-ray pictures with minimal performance deterioration. In medical imaging, where noise can obfuscate key information, this trait is very crucial.
- **Standard HT and Fast HT** had modest noise resistance, with performance reducing as noise levels increased, but maintaining adequate accuracy.

4.4. RL Agent Performance

- **Fractional HT**: In terms of RL agent performance, fractional HT once again took the lead, achieving the fastest convergence times and the best classification and anomaly detection accuracy in X-ray pictures. The capacity of the agent to make accurate judgements was aided by the extensive feature extraction that Fractional HT offered.
- **Adaptive HT**: outperformed Fractional HT in RL tasks, particularly in anomaly detection and classification. However, training periods were significantly longer due to parameter adjustment.
- In comparison to the other methods, **Fast HT and Standard HT** demonstrated middling RL agent performance, with slower convergence times and less precise anomaly identification.

4.5. Overall Performance

Based on the weighted average of the four measures, the Overall Score (Average) was determined. The findings are summed up as follows in Table 1:

Table 1: Performance Comparison of Hadamard Transform (HT) Techniques Across Key Metrics

Technique	Computational Efficiency	Feature Extraction	Noise Resistance	RL Agent Performance	Overall Score (Average)
Standard HT	3	4	3	3	3.25
Fractional HT	3	5	5	5	4.5
Fast HT	5	4	3	3	3.75
Adaptive HT	2	5	5	5	4.25

Key Findings:

- With an average score of 4.5, **Fractional HT** performed best overall, outperforming RL agents in feature extraction, noise resistance, and other areas.
- **Adaptive HT** scored 4.25 for its capacity to dynamically adapt to changing picture properties, but was less computationally efficient.
- With a score of 3.75, **Fast HT** was the most computationally efficient but performed mediocrely in other domains.
- The baseline approach, **Standard HT,** had a lower total score of 3.25 while providing balanced performance.

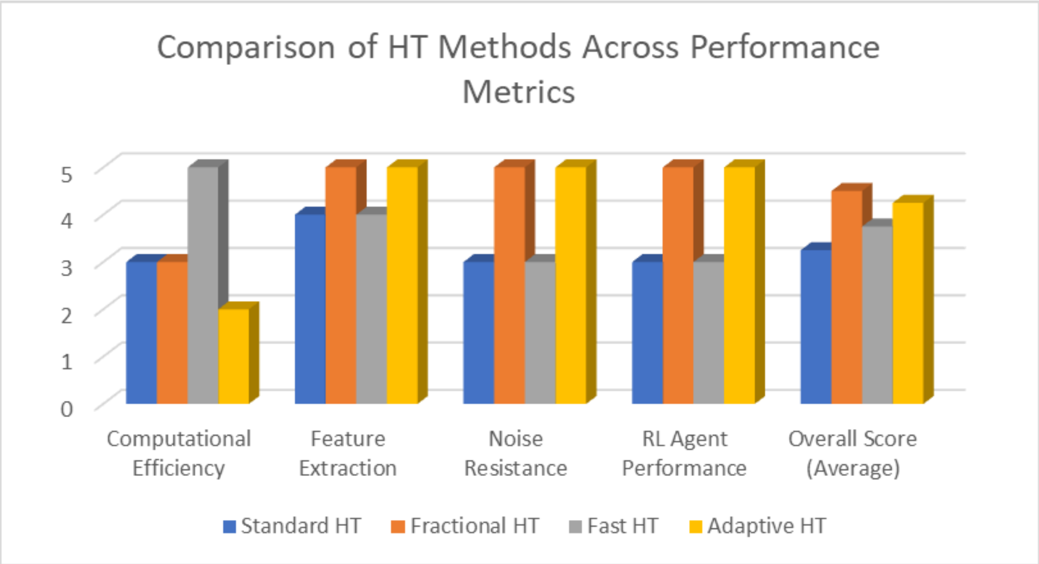

Fig 1: A comparative analysis of different HT methods across various performance metrics.

Four distinct HT techniques are compared using five important performance criteria, as seen in Fig. 1: computational efficiency, feature extraction, noise resistance, RL agent performance, and total score. A distinct coloured bar is used to symbolise each approach, making visual comparison simple. According to the graph, adaptive HT routinely performs better than the other approaches in the majority of areas, especially computational efficiency and noise resistance. Fractional HT may impair overall performance even if it has promise in feature extraction. While Fast HT gives a notable speedup with no effect on performance, Standard HT provides a reliable baseline. Fast HT is best suited for real-time applications that value computational speed, whereas Fractional HT is the best HT approach for applications needing high precision, thorough feature extraction, and robustness against noisy pictures, according to these findings. Although adaptive HT has a computational expense, it is perfect for situations where flexibility and noise robustness are critical.

5. CONCLUSION

This study examined four Hadamard Transform (HT) methods in reinforcement learning (RL) for X-ray image analysis: Standard HT, Fractional HT, Fast HT, and Adaptive HT. Applications needing high precision and robustness will benefit greatly from fractional HT's superior performance in feature extraction, noise resistance, and RL agent performance. Despite being less computationally efficient, adaptive HT demonstrated great flexibility and noise tolerance. Fast HT fared poorly in feature extraction and anomaly detection, but it was very efficient in computing. Standard HT lacked specialisation but offered balanced performance. Hybrid HT approaches should be investigated in future studies to combine the advantages of these methods, enhancing feature extraction and computing efficiency. Future studies need to explore hybrid HT strategies that integrate the advantages of both methods, enhancing feature extraction and computing efficiency. Enhancing HT's integration with sophisticated RL models, such as deep reinforcement learning (DRL), may also improve X-ray picture processing. For more thorough findings, next research might also address scaling concerns and assess these methods on a wider variety of medical imaging modalities.

REFERENCE

1. Hu M, Zhang J, Matkovic L, Liu T, Yang X. Reinforcement learning in medical image analysis: Concepts, applications, challenges, and future directions. J Appl Clin Med Phys. 2023 Feb;24(2):e13898. doi: 10.1002/acm2.13898. Epub 2023 Jan 10. PMID: 36626026; PMCID: PMC9924115.
2. Abdel-Aziz, M. M., Hosny, K. M., Lashin, N. A., & Fouda, M. M. (2021). Blind Watermarking of Color Medical Images Using Hadamard Transform and Fractional-Order Moments. *Sensors*, *21*(23), 7845. https://doi.org/10.3390/s21237845
3. Venkatachalam, Kv & Siuly, Siuly & Bacanin, Nebojsa & Hubalovsky, Stepan & Trojovsky, Pavel. (2021). An Efficient Gabor Walsh-Hadamard Transform Based Approach for Retrieving Brain Tumor Images From MRI. IEEE Access. PP. 1-1. 10.1109/ACCESS.2021.3107371.
4. Kasim Ö. Secure medical image encryption with Walsh-Hadamard transform and lightweight cryptography algorithm. Med Biol Eng Comput. 2022 Jun;60(6):1585-1594. doi: 10.1007/s11517-022-02565-5. Epub 2022 Apr 7. PMID: 35389195.

5. K. Venkatachalam, S. Siuly, N. Bacanin, S. Hubálovský and P. Trojovský, "An Efficient Gabor Walsh-Hadamard Transform Based Approach for Retrieving Brain Tumor Images From MRI," in IEEE Access, vol. 9, pp. 119078-119089, 2021, doi: 10.1109/ACCESS.2021.3107371.
6. Lei G, Lai W, Meng Q, Cui W, Liu H, Wang Y and Han K (2024) Low-sampling high-quality Hadamard and Fourier single-pixel imaging through automated optimization neural network. *Front. Phys.* 12:1391608. doi: 10.3389/fphy.2024.1391608