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RESEARCH PAPER **OPEN ACCES**

Optimization of Intelligent Grid Strength and Grid Ratio to Improve Pelvic Radiographic Image Quality in Digital Radiography

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Abstract

Pelvic radiography is an essential diagnostic procedure; however, its image quality is often degraded by scattered radiation, which reduces contrast and diagnostic accuracy. Conventional physical grids can reduce scatter but have limitations, including increased patient dose and workflow constraints, particularly in mobile radiography. The Intelligent Grid, a digital scatter correction technology, provides a promising alternative, yet the optimal combination of grid ratio and strength parameters remains unclear. This study aims to optimize the strength and grid ratio of the Intelligent Grid to improve the quality of pelvic radiographic images. This study introduces a novel quantitative optimization approach that systematically integrates grid ratio and strength variations within the Intelligent Grid system to enhance pelvic radiographic image quality in digital radiography. A quantitative experimental approach with a post-test only design was conducted using a mobile X-ray system, digital radiography, an Aero DR detector, and pelvic phantoms. Data were acquired by performing anteroposterior pelvic radiography exposures (60 kV & 10 mAs) with the Intelligent Grid. Strength variations (slightly strong, normal, slightly weak) and grid ratios (3:1, 6:1, 8:1, 10:1, 12:1) were applied to generate different parameter combinations. Image quality was evaluated quantitatively (histogram and SNR) and qualitatively through visual grading by three radiologists. Statistical analysis was performed using repeated ANOVA and Friedman tests. Statistical analysis showed significant differences ($p < 0.001$) in pelvic radiographic image quality across Intelligent Grid ratio and strength combinations. The 12:1 grid ratio with slightly strong strength yielded the highest mean SNR, balanced grayscale distribution, and top visual grading scores, confirming its optimal performance in enhancing image contrast and anatomical visibility of the iliac contour, acetabulum, and pubic symphysis. In conclusion, optimal adjustment of Intelligent Grid strength and grid ratio parameters can substantially improve pelvic radiographic image quality, providing a practical alternative to conventional physical grids in digital radiography.

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I. Introduction

When X-rays are used in pelvic radiography, the scatter radiation generated can account for 40-60% of detected signal, reducing contrast by approximately 30-50%, especially in thicker anatomical areas like the pelvis [1]. A substantial reduction in this decrease reduces the precision of diagnosis; obscures fine details; and may necessitate repeated exposition to increase patient dose [2]. In the traditional method of scatter radiation reduction, a physical anti-scatter grid is used to absorb the scattered radiation before it reaches the detector [3], [4]. However, there are several drawbacks to using these devices, including increased dose, alignment errors, and poor mobility during examinations [5], [6], [7]. Digital radiography has made it possible to create intelligent or virtual grid systems, which are software algorithms with scatter correction that emulate the physical grid's operation through image processing [8], [9]. It provides the ability to acquire images without a physical grid and achieve comparable contrast to that of utilizing refractive conventional imagery [10]. Several studies have reported that intelligent grids can reducethe scatter fraction by 30–50%, increase contrast by up to 40% compared with images without a grid [11], [12], and reduce the imaging dose by approximately 20% [13]. However, the effectiveness of scatter correction algorithms depends on software parameter settings. The grid ratio in the Intelligent Grid is a virtual parameter that represents the ratio between virtual lead strip height and

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interspace distance, similar to physics but implemented through an algorithm. The degree of scatter suppression applied by the software determines the grid strength, which balances the effects of contrast enhancement and noise amplification [14]. The combination of these determines the balance between contrast enhancement and noise or potential artifacts [15]. Experimental studies have shown that variations in grid ratio and strength can affect the signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR) in pelvic examinations [16].

Among all regions, the pelvic region experiences the most scattering due to tissue thickness and anatomical complexity [17]. Therefore, optimizing intelligent grid parameters is crucial to maintain diagnostic image quality without increasing dose. Several studies have demonstrated that the use of a virtual grid in the pelvis can result in image quality similar to physico-chemical grids, but this differs depending on the algorithm vendor and exposure conditions [18].

Unlike previous studies that primarily compared the presence or absence of virtual grids or evaluated a single level of grid ratio parameter without exploring various strength settings [18], [19], [20], resulting in these studies not providing comprehensive guidance for parameter optimization in clinical practice, particularly regarding the combined effects of grid ratio and strength variations within an intelligent grid system through simultaneous quantitative and qualitative image assessment. This study presents a systematic quantitative optimization framework that incorporates various grid ratios and strength levels within an Intelligent Grid system.

The novelty of this approach lies in evaluating the interaction effects between grid ratio and strength parameters using combined quantitative metrics (SNR and histogram distribution) and qualitative visual grading. There is no systematic study that utilizes both quantitative and qualitative methods to evaluate the combined interaction of grid ratio and strength parameters within an Intelligent Grid system, resulting in the development of clinically actionable optimization guidelines. An improved integrated framework can be used to identify an optimal parameter combination, rather than performing poorly on isolated parameters, resulting in more clinically actionable guidance for pelvic radiography protocols.

Based on this gap, this study aims to optimize the combination of intelligent grid strength and grid ratio to improve the image quality of digital pelvic radiographs. The contribution of this study lies in providing a systematic approach to optimizing Intelligent Grid parameters based on quantitative and qualitative image assessments. The finding is expected to help with the development of evidence-based clinical imaging protocols [21]. Specifically, this study contributes by: 1] Determining the optimal combination of grid ratio and strength parameters within the Intelligent Grid system to achieve superior image quality;2) Establishing evidence-based parameter recommendations applicable to clinical radiographic practice; 3) Conducting a comprehensive evaluation of image quality using both quantitative metrics (SNR and histogram analysis) and qualitative assessment through visual grading analysis (VGA) by expert radiologists.

This paper is structured as follows: Section II describes the research methodology, including the experimental design, research procedures, and image quality evaluation. Section III provides quantitative analysis and outlines the research findings. Section IV discusses the implications of the findings relative to previous studies and the study's limitations. Section V summarizes the main contributions and conclusions of this study, along with suggestions for future research.

II. Materials and Method

The objective of the research was to optimize the combination of intelligent grid strength and grid ratio parameters in a digital radiography system to improve the quality of pelvic radiographic images, as evaluated quantitatively and qualitatively. High-quality radiographic images are defined based on diagnostic standards that emphasize optimal contrast, adequate spatial resolution, and clear anatomical details without excessive noise, as stipulated in the European Guidelines on Quality Criteria for Diagnostic Radiographic Images and AAPM Report No. 116. The image quality parameters evaluated in this study include brightness (grayscale value), contrast (histogram distribution), and noise level (SNR) [22].

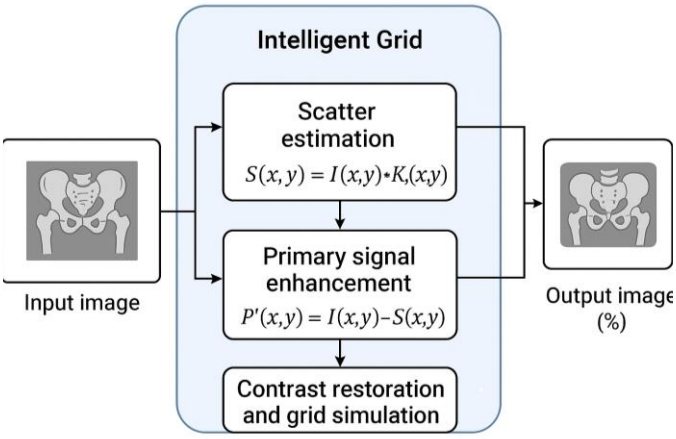


Fig. 1. Flowchart of process Intelligent Grid

One of the main factors that degrade image quality is scatter radiation, which reduces image contrast and sharpness. Therefore, Adaptive image processing algorithms that improve contrast and diagnostic accuracy require the implementation of a software-based scatter correction system, such as Intelligent Grid, which can mimic the functionality of an actual grid [23]. The Konica Minolta AeroDR Intelligent Grid System software performs scatter estimation, primary signal enhancement, contrast restoration (shown), and grid simulation as the four main stages of the scatter correction in the Intelligent Cloud: scatter estimation, primary signal enhancement, contrast restoration, and grid simulation as shown in Fig. 1. The total detected image ((I_total) is expressed as the sum of the primary signal (P) and scatter component (S), such that I_total =

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Table 1. Visual grading of qualitative image assessment

Score	Definition	Information
1	Poor	Anatomy unclear, artifacts visible, boundaries unclear, and cannot be analyzed
2	Inter mediate	Anatomy is fairly clear, few artifacts are visible, boundaries are clear, and can be analyzed
3	Good	Anatomy clear, no artifacts, boundaries clear with sharp structural lines, and easy to analyze

P + S. Scatter estimation is performed using low-pass filtering to approximate the scatter signal (Ŝ), and the corrected primary image is obtained by subtracting Ŝ from I_total (P̂ = I_total − Ŝ) [24], [25]. Contrast restoration is achieved through Contrast Limited Adaptive Histogram Equalization (CLAHE), which enhances local contrast while restricting noise amplification according to historical characteristics [26]. In this study, all images had their CLAHE parameters fixed (clip limit 2.0; 8x8 pixels in tile grid) to maintain consistency. The physical grid is emulated by simulating physical effects through a grid transfer function chosen from the appropriate grid ratio (3:1–12:1) and grid strength (slightly weak, normal, and slightly strong), resulting in an image that has the same visual quality as simulated images [27], [28], [29]. During exposure, the process is fully automated, and digital post-processing is performed without using a physical grid [30]. The Intelligent Grid workflow is shown in Fig. 1.

A. Research Design

This study used a quantitative experimental approach with a post-test only design. Data collection was conducted in the radiography laboratory of the Radiologic Imaging Technology Study Program, Universitas Muhammadiyah Purwokerto. The research instruments used were a PERLOVE PLX 101 C Mobile X-Ray Unit, digital radiography, an Aero DR detector with Intelligent Grid features, a computer workstation, stationery, and the image-J application. The research object was a pelvic radiographic phantom. A real human skeleton with similar organs and mobile joints is present in this anthropomorphic radiographic phantom, providing accurate X-ray images and instruction on proper alignment. Tissue-equivalent epoxy resin and calcium hydroxyapatite inserts are utilized to create a synthetic model that emulates the soft tissue and bone attenuation, which is in line with the use of phantoms in image quality and dose optimization studies [3], [15]. This research was conducted under controlled conditions, illuminated using standard AP (anteroposterior) pelvic exposure parameters according to the recommendations of the European Guidelines on Quality Criteria for Diagnostic Radiographic Images to ensure uniformity of results and diagnostic image quality [22]. The research sample was 16 AP pelvic radiographic images.

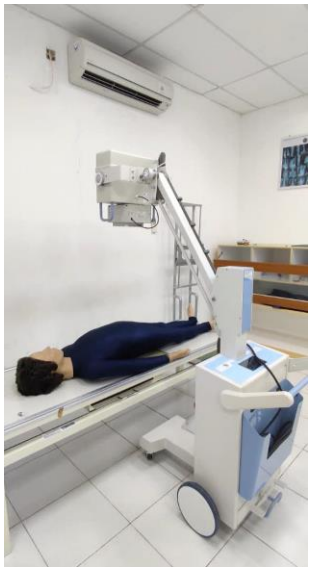


Fig. 2. Radiographic Image Acquisition with supine AP pelvic

B. Radiographic Image Acquisition

Radiographic images were acquired in pelvic anteroposterior (AP) projection using two methods: 1) Conventional physical grid (8:1 ratio); and Intelligent Grid software with grid ratio variations of 3:1, 6:1, 8:1, 10:1, and 12:1, each combined with suppression strengths of slightly weak, normal, and slightly strong. See Fig. 2, first, data entry was performed using a radiographic phantom for the pelvic radiography. Next, ensure the phantom is free of metal objects that could interfere with the imaging. Position the phantom on the examination table for the pelvic examination. The phantom was exposed with and without a physical grid for the AP pelvic examination (60kV and 10mAs). Five grid ratio variations were then applied to the two pelvic radiograph images on the intelligent grid (3:1, 6:1, 8:1, 10:1, and 12:1). The grid ratio (*r*) is defined as Eq. (1) [7] :

$$r = \frac{h}{D} \tag{1}$$

where *h* is height of lead strips, and *D* is distance between strips (interspace width). Three strength variations were applied to each image with the grid ratio variations mentioned above (slightly strong, normal, and slightly weak). Grid strength, also known as grid selectivity (*Gs*) is defined as Eq. (2) [31] :

$$G_s = \Sigma = \frac{T_p}{T_s} \tag{2}$$

where T_p is transmission of primary radiation through the grid, and T_s is transmission of scattered radiation through the grid. A total of 16 radiographic images were obtained, representing all parameter combinations (five grid ratios × three strength levels) plus one image using a physical grid as a reference. Each image was acquired under identical exposure conditions (60 kV and 10 mAs) using a standardized pelvic phantom to ensure uniformity and minimize external variability. The exposure parameters of 60 kV and 10 mAs were selected based on manufacturer recommendations for pelvic phantom imaging and European Guidelines, representing standard conditions that generate sufficient

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scatter for evaluating grid performance while avoiding detector saturation or excessive noise [22].

C. Radiographic Image Quality Assessment

Image quality evaluation was performed on 16 AP pelvic radiographs obtained using varying grid ratios (3:1, 6:1, 8:1, 10:1, and 12:1) and strength parameters (slightly weak, normal, and slightly strong). The selected grid ratios (3:1, 6:1, 8:1, 10:1, and 12:1) correspond to commonly used physical grid ratios in clinical radiography and are implemented as standard virtual configurations in Intelligent Grid systems [3]. The suppression levels used to adjust the scatter correction for object thickness and exposure conditions are represented by strength variations (slightly weak, normal, and slightly strong) [14]. The assessment involved two approaches: quantitative and qualitative. The quantitative assessment was performed using histogram analysis and signal-to-noise ratio (SNR) for each image using Image-J. The qualitative assessment was performed using visual grading analysis by a radiologist.

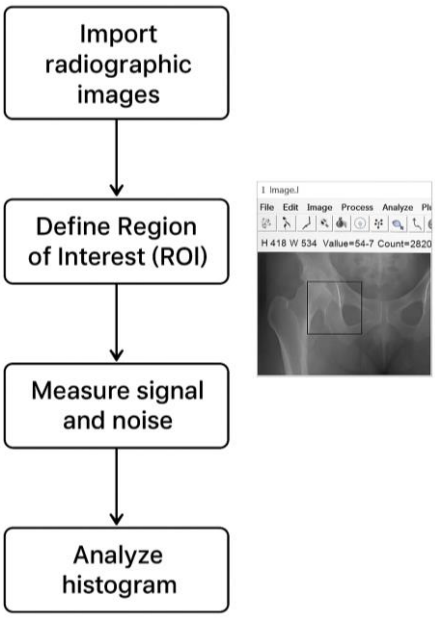


Fig. 3. Flowchart of Radiographic Image Quality Quantitative Assessment

1. Quantitative Assessment

SNR is the ratio of signal strength to noise level in a digital image. The primary objective of SNR computation is to quantitatively evaluate image quality, particularly in digital radiography systems research or testing. ImageJ (National Institutes of Health, USA) was utilized for quantitative analysis, enabling retrieval of digital image pixel data in 8-bit depth and DICOM format. To measure SNR, it was necessary to identify Regional Interests (ROIs) in three specific areas: the articular region (ischium), the hip joint (acetabulum-femoral head interface), and soft tissue ROI in homogeneous regions adjacent to the pelvis [3]. The selection of ROI was based on the same ROI sizes and anatomical landmarks across all images. To minimize variability between images, ROIs were positioned at the same pixel coordinates as the phantom anatomy to ensure consistency [32]. The SNR value is calculated using the following Eq. (3) [16]:

$$SNR = \frac{\mu_{signal}}{\sigma_{noise}} \quad (3)$$

where is μ_{signal} : the mean pixel intensity value in the anatomical ROI, and σ_{noise} : the standard deviation of the intensity in a homogeneous, object-free area. The higher the SNR value, the better the image quality because it indicates a greater signal-to-noise ratio [32]. Quantitative analysis is illustrated in Fig. 3. In this study, grayscale is used to describe the average gray value obtained from the histogram, while histometric analysis reveals the overall intensity distribution and dynamic range of the image, which are directly related to the performance of contrast and scatter suppression [32], [33]. The aim of this is to exhibit the number of pixels that a given intensity value permits us to determine the contrast, brightness, and dynamic range of radial images. To investigate the gray level distribution of radiographic images, histogram analysis was conducted with varying grid ratios and strength parameters. The image analysis was performed using an ROI equivalent to the FOV and the collimation region. By using the Analyze-Histogram function, ImageJ automatically determined the mean gray value and standard deviation. The mathematical formula for the histogram intensity i is given by Eq. (4) [34] :

$$p(i) = \frac{n_i}{N} \quad (4)$$

where is p(i) is probability of pixels with intensity i, n_i is number of pixels with intensity i, N is total number of pixels in the ROI.

2. Qualitative Assessment (Visual Grading)

Three radiologists blindly assessed pelvic radiographic images on a diagnostic monitor without information on exposure parameters or grid strength settings. Assessment was performed using a visual grading analysis (VGA) system using a three-level numeric scale (1–3) to assess the clarity of bony anatomy, joint spaces, and pelvic soft tissues (see Table 1). A three-level numeric scale (1–3) was selected to minimize observer variability and fatigue while maintaining sufficient sensitivity to detect clinically relevant differences. Similar scales have been widely used in phantom-based visual grading studies [20].

D. Data Processing and Analysis

Quantitative data (SNR and histogram) were processed by IBM SPSS Statistics 16. Normality testing was carried out using the Shapiro–Wilk test (n 50). Using a repeated-measures ANOVA, the differences between grid ratio and strength parameter combinations were tested on normally distributed data. Due to the same exposure conditions and pelvic phantom, this approach was chosen as it allowed each of the 16 radiographic images to function as a within-subject condition in a 'controlled repeated-measures design'. Non-parametric methods were employed in lieu of repeated-measures ANOVA for non-normally distributed data obtained from

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qualitative assessments (VGA) using the Friedman test. The objective of independent duplication of each quantitative and qualitative measurement was to increase statistical robustness and minimize random error. The best-balanced Intelligent Grid parameter combination between noise suppression, contrast enhancement, and anatomical visibility was determined using statistical analysis. All findings were interpreted in accordance with the European Guidelines on Quality Criteria for Diagnostic Radiographic Images and AAPM Report No. 116 to ensure methodological consistency and clinical relevance qualitative assessment through visual grading analysis (VGA) by three radiologists

RESULT

In this study, a total of 16 AP pelvic radiographic images were analyzed, consisting of one image acquired using a physical grid (8:1) and 15 images processed using the Intelligent Grid with variations in grid ratio (3:1, 6:1, 8:1, 10:1, and 12:1) and strength levels (slightly weak, normal, and slightly strong). Image quality was evaluated using quantitative methods (histogram, grayscale, and signal-to-noise ratio [SNR]) and.

A. Quantitative Image Assessment

1. Histogram and Grayscale Analysis

The histogram analysis revealed distinct variations in grayscale distribution between physical grid-generated images and those processed with the Intelligent Grid. A relatively small distribution in the histogram was produced by the physical grid (8:1), indicating lower contrast and limited dynamic range. Conversely, in Intelligent Grid images, the distribution of histograms was much wider and more prominent at greater grid ratios (10:1 and 12:1) (see Fig. 4), suggesting higher contrast and grayscale variation. Quantitatively, the use of Intelligent Grid led to a quantum increase in grayscale dynamic range from 15 to 18%, which is comparable to the physical grid. The most desirable histogram distribution, which was wide and symmetrical without excessive clipping at a 12:1 grid ratio with slightly strong strength, suggested that contrast enhancement was achieved while maintaining noise stability.

2. SNR Measurement

The SNR analysis (see Table 2) showed a consistent

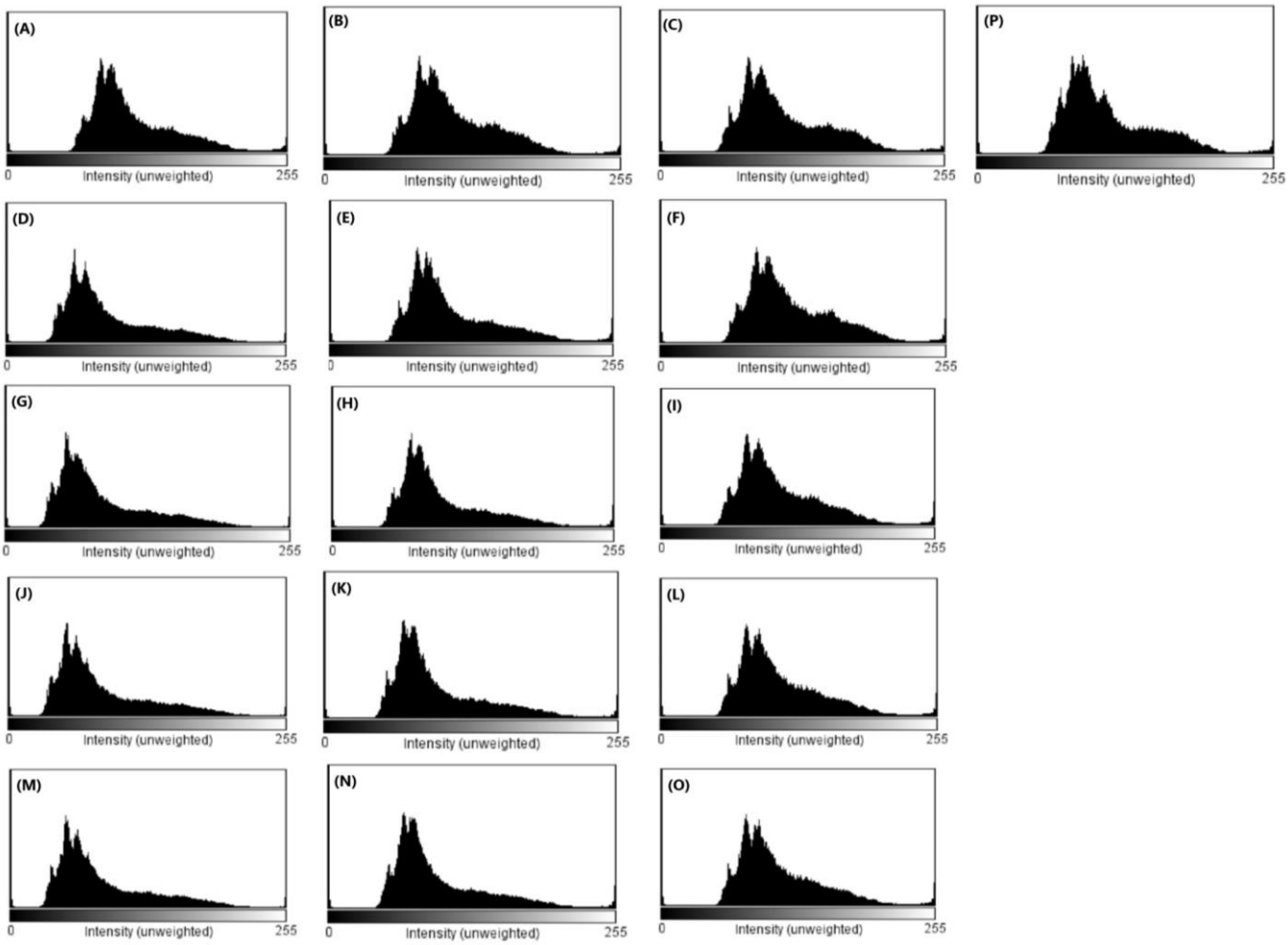


Fig. 4. Histogram of PA pelvic radiographic images between using intelligent grid variation of grid strength and ratio (A) slightly strong ratio 3:1, (B) normal ratio 3:1, (C) slightly weak ratio 3:1, (D) slightly strong ratio 6:1, (E) normal ratio 6:1, (F) slightly weak ratio 6:1, (G) slightly strong ratio 8:1, (H) normal ratio 8:1, (I) slightly weak ratio 8:1, (J) slightly strong ratio 10:1, (K) normal ratio 10:1, (L) slightly weak ratio 10:1, (M) slightly strong ratio 12:1, (N) normal ratio 12:1, (O) slightly weak ratio 12:1, and (P) physical grid ratio 8:1

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increase in image quality with increasing grid ratio and strength. In the ischium region, the SNR increased from 308.9 (physical grid 8:1) to 390.28 at a grid ratio of 12:1, with slightly stronger strength, representing an improvement of approximately 26.3%. In the joint space region, SNR increased from 297.58 to 365.29 (approximately 22.8% increase) (see Table 3). However, in the soft tissue region, SNR decreased from 130.47 (physical grid) to 111.46 at the highest setting (12:1 slightly strong), indicating a decrease of around 14.6%, which implies greater sensitivity to noise augmentation in low-contrast areas. Overall, the SNR values obtained by the Intelligent Grid with a grid ratio of 12:1 and slightly strong strength were the highest across all anatomical regions. The SNR values for each parameter combination varied significantly (p 0.001) in a statistical analysis using repeated-measures ANOVA, which indicated that grid ratio and strength have an important impact on image quality (see Table 3).

B. Qualitative Image Assessment (Visual Grading Analysis)

Three radiologists conducted a visual grading analysis that revealed quantitative results consistent with the findings. Optimal visualization of anatomical structures was indicated by the Intelligence Grid's 12:1 grid ratio and slightly strong strength, with images achieving the highest visual scores (score = 3). In comparison, images acquired using the physical grid (8:1) were generally rated as moderate quality (score = 2). The highest scores were associated with improved visualization of key anatomical structures, including the iliac contour, acetabulum, and pubic symphysis. Table 4 demonstrates that the Friedman test revealed that there was a significant difference (p 0.01) between parameters variations, indicating that perceived image quality is significantly affected by the variation of Intelligent Grid parameters.

III. DISCUSSION

The pelvic radiographic image quality was significantly influenced by changes in Intelligent Grid parameters, such as grid ratio and strength (p 0.001). These results are consistent with previous studies stating that parameter settings in scatter correction algorithms strongly influence image quality [17], [35].

In conventional radiography, scatter reduction is achieved using physical grids, which improve contrast by absorbing scattered radiation [11], [12]. However, higher grid ratios, while more effective in reducing scatter, also require higher exposure, leading to increased patient dose [31]. Therefore, there is always a trade-off between image quality and radiation dose, and grid selection must be adjusted based on patient anatomy and examination conditions [3]. Virtual and intelligent grids have been developed to overcome these limitations [2]. These technologies aim to replace physical grids by using digital scatter correction. Previous studies have shown that Virtual Grid can produce image quality comparable to physical grids while reducing radiation dose [12]. This makes Intelligent Grid particularly useful in mobile radiography, where physical grid use is limited. This study further confirms that not only the use of Intelligent Grid, but also the combination of grid ratio and strength parameters, plays an important role in determining image quality. Therefore, proper parameter optimization is essential.

A. Grayscale Value Distribution

Compared to physical grids, the intelligent grid shows an increase in grayscale distribution of around 15-18% according to histogram analysis. The best result was obtained at a grid ratio of 12:1 with slightly stronger strength, which produced a wider and more balanced histogram. This indicates better contrast and clearer differentiation of anatomical structures. Similar findings have been reported in previous studies [33], [36].

Table 2. The results of the calculation of the SNR of PA pelvic radiographic images between using a physical grid and an intelligent

Grid-Type	Ratio	Strength	SNR Anatomy (μ/σ)		
			Ischium	Joint space	Soft tissue
Physical	8:1	-	308.9	297.58	130.47
Intelligent Grid	3:1	Slightly strong	347.75	325.95	147.49
		normal	302.28	281.94	132.88
		Slightly weak	338.92	307.9	142.6
	6:1	Slightly strong	352.15	332.5	136.29
		normal	322.22	300.24	129.2
		Slightly weak	341.12	317.2	130.1
	8:1	Slightly strong	360.32	342.79	128.29
		normal	328.72	319.38	121
		Slightly weak	351.52	326.21	126.1
	10:1	Slightly strong	380.18	359.21	117.56
		normal	361.67	333.31	113.3
		Slightly weak	371.42	339.48	115.3
	12:1	Slightly strong	390.28	365.29	111.46
		normal	374.67	346.34	100.3
		Slightly weak	380.67	354.2	110.45

A good histogram has a wide and symmetrical distribution without too much clipping, which indicates high contrast but low noise with equal brightness [31], [35]. This characteristic is clearly illustrated in Fig. 3, displaying the comparison of gray level distributions between images processed by the Intelligent Grid (with different strength levels) and those obtained from a physical grid (8:1).

As shown in Fig. 3, an image from Intelligent Grid displays increased intensity with a sharp change in the peak of the histogram, suggesting better separation between structures after correction by scatter and restoration of contrast. By utilizing CLAHE for scatter estimation, suppression, and contrast enhancement, the intelligent Grid system's algorithmic process can account for this effect. Combined, all these processes result in higher image contrast and grayscale differentiation. These results are consistent with Gossye

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et al. [1] and Sayed et al. [2], who found that software-based scatter correction improves both contrast and anatomical visibility. Additional research has shown that the use of advanced scatter correction techniques can enhance the visualization of soft tissues by extending the grayscale range [33], [36]. Finally, previous work has established a strong correlation between increased CNR and changes in histogram distribution and grayscale expansion, as well as higher subjective image quality scores from radiologists [21]. Therefore, the application of Intelligent Grid not only serves as a viable alternative to physical grids but also provides additional diagnostic advantages by enhancing grayscale distribution and highlighting fine anatomical details, such as trabecular patterns in pelvic bone structures.

Table 3. Results of repeated ANOVA (Within-Subjects Effects) on PA pelvic radiographic images

Variable pelvic AP image	Sig. *(p-value)*
Grid physical (ratio 8:1)	<0.001
Intelligent grid (ratio 3:1, slightly weak)	
Intelligent grid (ratio 3:1, normal)	
Intelligent grid (ratio 3:1, slightly strong)	
Intelligent grid (ratio 6:1, slightly weak)	
Intelligent grid (ratio 6:1, normal)	
Intelligent grid (ratio 6:1, slightly strong)	
Intelligent grid (ratio 8:1, slightly weak)	
Intelligent grid (ratio 8:1, normal)	
Intelligent grid (ratio 8:1, slightly strong)	
Intelligent grid (ratio 10:1, slightly weak)	
Intelligent grid (ratio 10:1, normal)	
Intelligent grid (ratio 10:1, slightly strong)	
Intelligent grid (ratio 12:1, slightly weak)	
Intelligent grid (ratio 12:1, normal)	
Intelligent grid (ratio 12:1, slightly strong)	

B. SNR Value

The increase in grid ratio and strength was found to have a positive impact on SNR, as well as image contrast, according to the quantitative results. At a grid ratio of 12:1 with some strong strength, the highest SNR value (390.28) was found at 69.6% greater than that of the physical grid (308.9), as shown in Table 2.

Hence, it is evident that higher levels of scatter suppression enhance the primary signal while reducing the noise contribution, especially in high-contrast regions such as bone. Earlier studies have shown that software-based scatter correction can significantly enhance SNR and contrast in digital radiography [18], [36], [37]. Increasing grid ratios and stronger suppression levels are consistent with the increasing SNR observed in Table 2 across all parameter combinations. By increasing the ischium ROI from roughly 308 (physical grid 8:1) to 390 (12:1, slightly strong), it was demonstrated that the Intelligent Grid is capable of reducing scatter-related noise and improving signal quality. The SNR enhancement can be demonstrated to exceed 25% compared to unscattered images by using scatter correction algorithms, as reported by Sakaltras et al. [18] and Lee [36]. However, this progress is not consistent among all tissues. In low-contrast soft tissue, the SNR decreased to approximately 14.6% at higher suppression levels. Due to this phenomenon, a significant amount of scatter correction can increase processing noise, particularly in regions with low attenuation contrast. Prior research has revealed that aggressive scatter suppression can increase noise and obscure subtle artifacts in soft-tissue visualization, as reported elsewhere [6], [38]. Soft tissue is expected to have lower SNR values than bone due to reduced inherent contrast and increased noise sensitivity following image processing [18], [34].

Parameter optimization is necessary to balance the improvement of contrast with the control of noise, as shown by these results. A high level of suppression can lead to an increase in noise, while a low level causes scattered noise [3], [18]. Earlier studies concur with these findings. According to Abdi et al. [37], virtual grids provide higher SNR than physical grid systems, which is not the case for other methods. Jreije et al.[38] demonstrated that image quality can be improved by altering parameters while maintaining dose dependence. Intelligent Grid reduces scatter at low ratios (3:1) and improves image quality without additional exposure with a higher ratio (12) for optimal image composition [1].

Therefore, to achieve optimal results, Intelligent Grid parameters, such as strength, must be adjusted based on patient anatomy and object thickness. A high level of suppression may cause an upsurge in noise and artifacts, whereas inadequate suppression lowers contrast [3], [18]. This study found that the setting (12:1, slightly strong) produced higher SNR and better anatomical visualization, which was consistent with previous research on high-scatter regions [12]. Despite concerns about patient safety, Intelligent Grid can be used as an adaptable and flexible solution that lowers

Table 4. The results of the Friedman test of the overall anatomy of the PA pelvic radiographic image

Variable pelvic AP image	Sig. *(p-value)*
Grid physical (ratio 8:1)	<0.001
Intelligent grid (ratio 3:1, slightly weak)	
Intelligent grid (ratio 3:1, normal)	
Intelligent grid (ratio 3:1, slightly strong)	
Intelligent grid (ratio 6:1, slightly weak)	
Intelligent grid (ratio 6:1, normal)	
Intelligent grid (ratio 6:1, slightly strong)	
Intelligent grid (ratio 8:1, slightly weak)	
Intelligent grid (ratio 8:1, normal)	
Intelligent grid (ratio 8:1, slightly strong)	
Intelligent grid (ratio 10:1, slightly weak)	
Intelligent grid (ratio 10:1, normal)	
Intelligent grid (ratio 10:1, slightly strong)	
Intelligent grid (ratio 12:1, slightly weak)	
Intelligent grid (ratio 12:1, normal)	

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compression levels for thin or pediatric patients while maintaining image quality [20],[30].

C. Visual Grading Analysis (VGA) and Nonparametric Analysis

Both quantitative and qualitative results from visual grading analysis (VGA) were in line with the general relationship between SNR and contrast, as well as their correlation with radiologist assessment. The highest VGA scores (score = 3) were obtained at the optimal parameter (12:1, slightly strong), with a statistically significant difference ($p < 0.001$) observed in Table 4, This suggests that parameter variation has broader implications for perceived image quality. Radiologists at this location were able to produce more detailed depictions of significant anatomical structures, including the ilium, acetabulum, and pubic symphysis (see Fig. 5). The outcomes indicate that enhancements in SNR and grayscale distribution directly impact anatomical visibility and diagnostic confidence.

These findings are in line with those of earlier studies. Virtual Grid can achieve image quality equivalent to that of physical grids, as shown by Gossye et al. [1], while Sayed et al. [2] drew attention to the

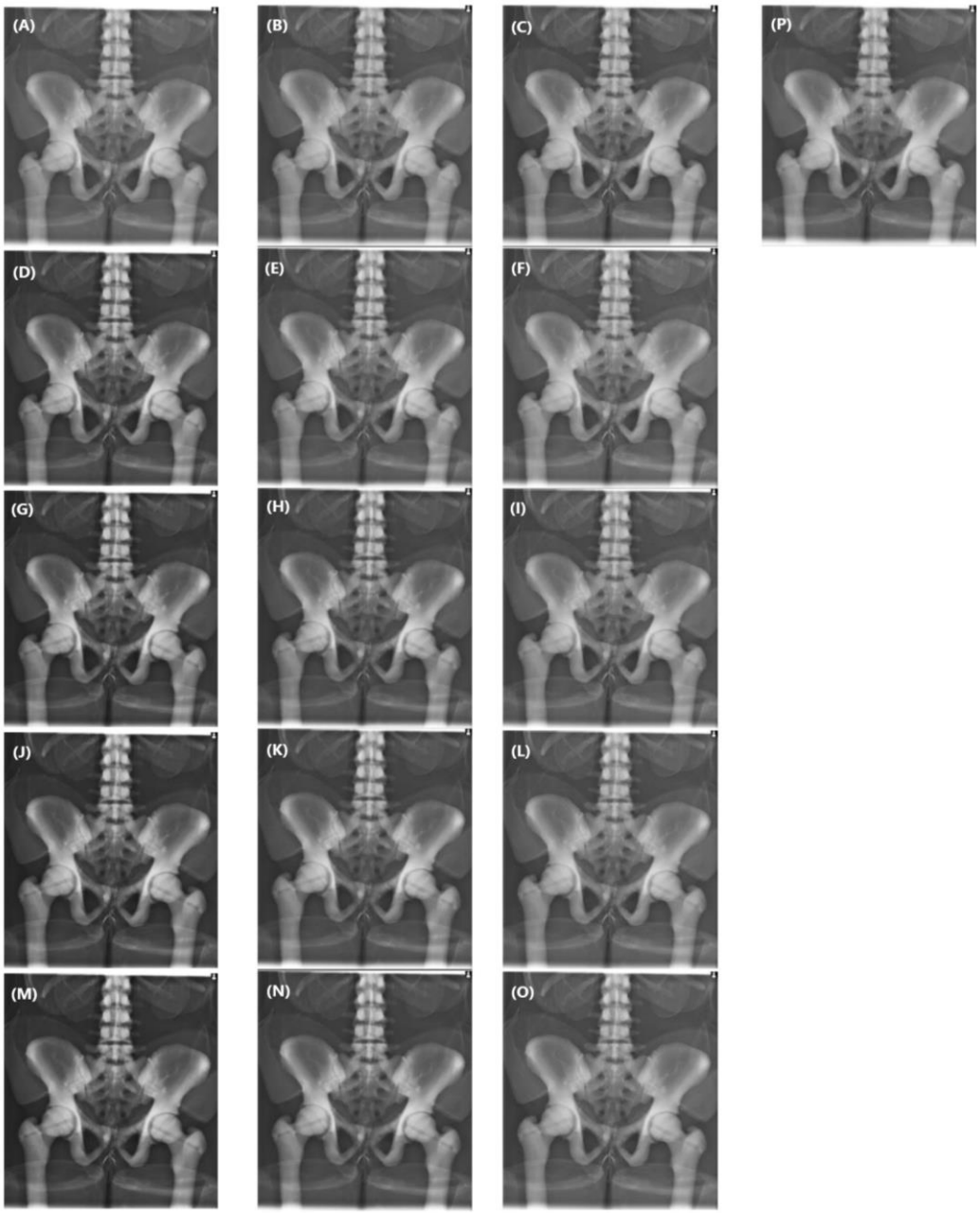


Fig. 5. AP projection pelvic radiographic images performed between using intelligent grid variation of grid strength and ratio (A) slightly strong ratio 3:1, (B) normal ratio 3:1, (C) slightly weak ratio 3:1, (D) slightly strong ratio 6:1, (E) normal ratio 6:1, (F) slightly weak ratio 6:1, (G) slightly strong ratio 8:1, (H) normal ratio 8:1, (I) slightly weak ratio 8:1, (J) slightly strong ratio 10:1, (K) normal ratio 10:1, (L) slightly weak ratio 10:1, (M) slightly strong ratio 12:1, (N) normal ratio 12:1, (O) slightly weak ratio 12:1, and (P) physical grid ratio 8:1

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effect of parameter configuration on scatter correction. The reduction of noise caused by scatter is a key factor in improving contrast and visual clarity, as reported by Lisson [12] and confirmed by other researchers. Images lacking scatter correction tend to display more artifacts and minimize the visibility of fine anatomical details [9], [23], [39]. However, at more powerful contrasts, some pictures displayed minor artifacts such as slight texture lift or faint linear patterns in homogeneous regions. Earlier studies have reported over-enhancement, as evidenced by these effects [40]. Although not affecting diagnosis, these artifacts emphasize the need for careful parameter selection to prevent potential degradation in the interpretation of soft tissues [6].

Intelligent Grid has been proven to maintain image quality while also reducing dose, despite this limitation [7], [8]. The results showed a 26.3% increase in SNR, which supports earlier research that previously demonstrated improvements of more than 20-25% using scatter correction techniques [18], [37]. Therefore, this study not only confirms previous results but also extends them by evaluating the combined effect of grid ratio and strength, providing a more practical framework for optimizing image quality in clinical radiography [20].

D. Clinical Implications and Limitations

In clinical practice, Intelligent Grid can serve as a replacement for physical grids, particularly in mobile radiography. The parameter (12:1 slightly strong) is the most suitable for achieving high image quality while minimizing radiation exposure [1], [8], [13]. The ALARA principle is reinforced in radiology practice. Improvements in physical images have a direct impact on diagnostic quality, as evidenced by the consistency of SNR and VGA results with qualitative outcomes [12]. However, this study has limitations. Due to the use of a phantom, these results cannot be broadly generalized in clinical settings where patients have different physical traits. The absence of a direct measurement method for radiation dose hindered the quantitative assessment of dose efficiency, which is still crucial in radiographic optimization. Only pelvic radiography was used in this study, and further investigation is necessary to determine the applicability of the findings to other anatomical areas. In addition, other factors, such as patient size variability and clinical conditions, were not fully investigated, and the relatively high implementation cost of Intelligent Grid technology may create challenges for resource-sparing healthcare facilities.

E. Future Research

Moreover, future research would need to include clinical validation of patient data, integration of direct dose measurements (mGy), and development of adaptive or AI-based optimization algorithms for automatic parameter selection across different imaging conditions, as suggested by recent developments in digital radiography and scatter correction technologies. Artificial intelligence's potential to incorporate Intelligent Grid systems from a technological perspective is significant, as it offers the possibility of automatically altering parameters based on patient anatomy, resulting in more efficient and safe imaging workflows.

According to this study, the most favorable result is achieved by optimizing the parameter (12:1, slightly strong) in the Intelligent Grid, which reduces scatter, enhances contrast, and expands the grayscale distribution. These findings indicate that while Intelligent Grid improves objective image quality, it also enhances clinical interpretability, making it a viable substitute for physical grids, particularly in high-scatter examinations like pelvic radiography, and upholding the ALARA principle to prevent unnecessary radiation exposure while maintaining diagnostic quality.

IV. Conclusion

This study optimized the strength and grid ratio of the Intelligent Grid to improve pelvic radiographic image quality. Statistical test results showed a significant difference ($p < 0.001$), with the optimal combination of a 12:1 grid ratio and slightly strong strength resulting in the best visibility of the ilium, acetabulum, and pubic symphysis. Quantitatively, the use of the Intelligent Grid increased the average SNR by ±25% and expanded the grayscale histogram range by ±18%, indicating improved contrast and fine anatomical detail. This technology also suppresses noise and supports the ALARA principle with the potential for radiation dose reduction. However, this optimal combination cannot be generalized to all pelvic anatomical thicknesses because the performance of the Intelligent Grid can vary depending on patient habitus and exposure conditions. Further research is recommended to include more diverse patient anatomies and thicknesses, analyze the received dose, and integrate deep learning-based adaptive algorithms for automatic optimization in various clinical applications.

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The bibliographic information in the reference list has been corrected and completed. No changes have been made to the scientific content, results, or conclusions of this article.

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