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Impact of exposure parameters on CT image distortion: Clinical study at Al-Sadr educational hospital, Najaf, Iraq

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Abstract
In this research study, the exposure parameters of kilovolt-peak (kVp) and milliampere-second (mAs) were recorded for 20 samples collected from patients who visited Al-Sadr Educational Hospital in Najaf, Iraq, during the period from February to April 2024, which this study aimed to investigate the impact of these exposure parameters on the computed tomography (CT) machine's image distortion and, consequently, the accuracy of diagnosis. It was found that these exposure parameters are closely related to the accuracy of the resulting image at different rates from one examination to another, so this all leads to the presence of a degree of distortion in the resulting radiographic image, which in turn generates diagnostic errors that affect the treatment plan, which necessitates reviewing the examination protocols of the CT machine to reduce distortion in the radiographic image while maintaining a low absorbed dose, as well as using artificial intelligence (AI) in processing radiographic images to increase image accuracy and thus obtain a better diagnosis.

Keywords: Image distortion, diagnostic accuracy, CT machine, kVp, mAs

1. Introduction

The computed tomography (CT) machine is one of the most important technical machines invented in the field of radiology, as it allows for high-resolution imaging of the body's internal structures without the need for surgical intervention, which technology was developed in the early 1970s by British engineer Godfrey Hounsfield, who won the Nobel prize in physiology or medicine in 1979 for his invention [1, 2]. CT scanning technology relies on the principle of using X-rays at multiple angles, accompanied by advanced computer processing, to obtain a detailed cross-sectional image of the body's internal organs, which enables doctors to accurately detect: tumors, clots, internal bleeding, and other conditions, that has made it a primary tool used in: hospital emergency rooms, specialized clinics, oncology centers, and others [3, 4].

CT technology has evolved significantly from single-slice machines to multi-slice machines (such as 64 slices), resulting in a reduction in imaging time and an increase in accuracy, which has contributed to a decrease in the radiation dose absorbed by patients [5, 6]. CT scans are used to diagnose and evaluate a wide range of medical conditions, including strokes, cerebral hemorrhages, heart disease, appendicitis, tumors, lung diseases, vesicoureteral intussusception, and other conditions, these scans are also used during surgical procedures, such as biopsies and fluid drainage, as well as to monitor the effectiveness of treatments, including cancer [7-9].

The CT technique is distinguished by its ability to provide accurate anatomical information about the area of the body to be diagnosed [10, 11]. Despite the benefits of CT, some risks warrant caution when using it repeatedly; the most important of these risks is exposure to ionizing radiation, which can lead to cumulative effects within the body over the long term. Therefore, it is necessary to reduce the amount of radiation absorbed by the body [12-14].

Modern techniques such as spectral CT and dual-energy CT have shown the possibility of obtaining additional physiological information by sorting materials and improving contrast while maintaining low radiation doses [15, 16]. In addition, artificial intelligence (AI) and machine learning techniques have been introduced to improve the accuracy of interpreting the resulting images, even at low radiation doses, which helps speed up reading time and reduce human error [17-19].

CT has become a staple in healthcare, with different protocols used depending on the area of the body to be examined, such as the head, chest, abdomen, and spine, whose guidelines relate to the technology used and the amount of absorbed dose [20-22]. CT technology is expected to witness further innovations in the future in terms of improving algorithms and developing hybrid imaging systems to achieve more clinical and therapeutic applications [23, 24].

This study investigated the effect of the CT exposure parameters on the accuracy of the resulting radiography, classifying them into several distortion types, which was accomplished by analyzing images of 20 clinical cases at Al-Sadr Educational Hospital in Najaf, Iraq.

2. Exposure Parameters

The two parameters, kilovoltage-peak (kVp) and milliampere-seconds (mAs), are fundamental exposure factors controlled by the radiologist to improve image quality while minimizing the patient radiation dose. Also, adjusting kVp and mAs settings based on the requirements of specific imaging and properties of the patient is critical for realizing quality diagnostic images with contrast appropriate and exposure convenient [2-4].

2.1 Kilovoltage-peak

The kVp is the peak voltage applied to the X-ray tube during an exposure, it determines the energy level of the X-ray photons produced, which impacts their power of penetrating and contrast in CT images, higher settings of kVp lead to higher energy of X-rays that can penetrate of thicker body tissues but may reduce images contrast in some cases [2-4].

2.2 Milliampere-second

The mAs is the product of the tube current measured in milliamperes (mA), the exposure time measured in seconds (s), it determines the quantity of X-rays produced during an exposure, which impacts the overall brightness and density of CT images, increasing of mAs lead to increases the number of X-ray photons that can higher image density with higher radiation dose to the patient [2-4].

3. Classification and Explanation of CT Artifacts

The CT is the cornerstone of the modern medical imaging field because of its high spatial resolution and ability to display internal anatomical structures in detailed cross-sectional images. As with all imaging techniques, CT imaging is not immune to the appearance of artifacts, defined as unintended changes or deviations in the reconstructed image that do not reflect the true anatomical or pathological reality. These artifacts can arise as a result of physical or technical factors, or due to patient movement, and can be negatively impact image quality, leading to reduced diagnostic accuracy or even misleading results, so understanding the nature, sources, and classification of artifacts is essential for radiologists, medical physicists, and radiographers, this is all to ensure accurate image interpretation and optimize examination settings [2-4].

A classification and explanation of the most common artifacts in CT imaging will be presented: noise, beam hardening, partial volume effect, motion artifact, and metal artifact [2-4].

3.1 Noise

The noise in CT images is a random fluctuation in pixel intensity that does not represent any real anatomical detail and usually appears as graininess or irregular spots in the image. The technical reasons include: using low mAs or kVp values, which results in fewer photons reaching the detector; high electronic resistance in the detectors; increased thickness of the CT slices, especially in large-volume cases [2-4].

3.2 Beam Hardening

The beam hardening in CT images is the loss of linearity in the image response due to absorption of low-energy radiation within the body, resulting in distorted pixel density, especially around bone. The technical reasons include: Polychromatic X-ray beams pass through dense materials such as bone; the lower-energy photons are rapidly absorbed, making the remaining beam harder, i.e., more energetic [2-4].

3.3 Partial Volume Effect

The partial volume effect in CT images occurs when a single voxel contains more than one tissue type. The average value between these structures is calculated, resulting in blurred details or inaccurate boundaries. The technical reasons include: the use of large slice thicknesses; intersections between structures of different densities, such as bone and soft tissue [2, 3].

3.4 Motion Artifact

The motion artifact in CT images appears as a blur or double lines due to patient movement during the scan, causing loss of detail. The technical reasons include: patient movement, voluntary and involuntary, such as breathing and coughing; long imaging time and poor fixation; lack of coordination between phases of respiration and imaging, especially in imaging of chest and abdomen [2-4].

3.5 Metal Artifact

The metal artifact in CT images is the appearance of distorted black and white lines around metallic implants such as stents and prostheses. The technical reasons include: inhomogeneity of absorption and refraction of X-ray beam around the metal; severe beam hardening, as well as photon starvation; noise in image reconstructions because of the difference in large density [2-4].

4. Artificial Intelligence and CT Artifact

The AI techniques have become increasingly important in medical imaging, especially in CT images, through the use of deep learning algorithms and artificial neural networks, which can interpret the images with better accuracy and efficiency, enabling automatic recognition of different artifact types, such as noise, metal artifacts, and motion artifacts. Also, the AI techniques are used to reconstruct the images in sorts that maintain high quality even at low doses of kVp and mAs, reducing patient radiation exposure without compromising diagnostic accuracy. Additionally, the AI techniques are used to predict the quality of an image based on scan settings such as kVp and mAs, to provide automatic adjustment recommendations to reduce the probability of artifacts. Therefore, the integration of AI with imaging technologies can enhance diagnostic accuracy, reduce the need for re-examination, and support more objective clinical decision-making [17-19].

5. Materials and Methods

This study strictly adhered to the ethical principles and guidelines set by the Committee of Ethics in Al-Sadr Educational Hospital, Najaf, and all participants were informed of the procedures and objectives of this study to obtain their consent to include their data in this study.

5.1 Equipment and Imaging Techniques

The CT scanner used is Siemens Healthineers, Germany, model SOMATOM Definition AS, presented in Figure 1. This machine features include: a 64-slice scanner; a wide gantry aperture of 70 cm in diameter; holds up a patient weight of 200 kg or little more; a rotation speed of 0.33 s/rotation; and a spatial resolution of up to 0.33 mm, this all makes it suitable for three-dimensional (3D) imaging of body with high resolution [2, 4, 25].

Furthermore, it features adaptive 3D dose modulation and additional technologies such as: combined applications to reduce exposure and four-dimensional dose modulation (CARE Dose4D), for intelligent dose adjustment; and z-Sharp, which improves spatial resolution and reduces image noise without increasing radiation dose [4, 5, 25]. Additionally, it supports advanced AI-based reconstruction algorithms [17-19, 24].

This CT scanner is widely used in cardiovascular imaging, oncology imaging, and neurological imaging [2, 4, 16]. Therefore, it is a perfect choice in clinical cases that need a balance between scan speed, image quality, and radiation decrease.

Fig 1: Picture of the SOMATOM Definition AS machine in Al-Sadr Educational Hospital, Najaf, Iraq.

5.2 Participants and Inclusion Criteria

The 20 samples were collected from patients who visited Al-Sadr Educational Hospital in Najaf between February and April 2024 for CT scans in the Department of Radiology, for which the data were available, as they consented, and could be analyzed for their diagnostic and subsequent treatment procedures.

Data were categorized based on participants' age and gender, as well as exposure parameters: kVp and mAs, to determine the type of distortion in the resulting radiographic image, including: noise, beam hardening, partial volume effect, metal artifact, and motion artifact, as presented in Table 1. Additionally, statistical analysis of the data was performed to calculate: minimum, maximum, mean, median, and standard deviation, as presented in Table 2.

5.3 Distortion Analysis and Exposure Criteria

A systematic approach was used to evaluate the data of the radiographic distortions that impact image quality and diagnostic results.

5.3.1 Classification and Assessment of Artifact

The artifacts were classified into five common types in CT imaging: noise, beam hardening, partial volume artifact, motion artifact, and metal artifact, as presented in Table 1. The classification was based on the scientific literature [2-4] and the experience of radiologists in the Department of Radiology. Also, radiologists determined visually the type of distortion present in the CT images. Therefore, their assessments were used primarily to estimate the impact of the artifacts on image quality.

5.3.2 Correlation to Exposure Parameters

The kVp and mAs values used for each case during the examination were recorded. By using Microsoft Excel, statistical analysis was performed to understand the relationship between exposure parameters: kVp and mAs, and the type of artifacts present in the CT images, as presented in Table 2. One-way analysis of variance (ANOVA) was used to estimate the impact of kVp and mAs on the type and severity of artifacts, and the results of the ANOVA for kVp and mAs parameters related to distortion types, as presented in Tables 3 and 4, respectively.

6. Results and Discussion

The 20 authorized samples, 10 males and 10 females, were collected from patients who underwent CT scanning at Al-Sadr Educational Hospital in Najaf. Table 1 presented the different ages of the participants, from young to elderly, and the kVp, and the mAs used, all according to the followed protocol, to which this, the types of image distortion were classified into: noise, beam hardening, partial volume effect, metal artifact, and motion artifact.

According to Table 2, the statistical results show that the ages of the participating patients were between 23 and 68 years, with a mean of 43.55 years, a median of 41.5 years, and a standard deviation of 11.98, which indicates that most of the participants' ages were approximately between 43.55 ± 12 years, i.e., between 31.5 and 55.5 years. As for kVp, the statistical results were between 100 and 137 kV, with a mean of 118.1 kV and a median of 117.5 kV, resulting in a standard deviation of 10.66, which indicates that most tests were conducted using an electrical voltage close to 118 kV, with reasonable variation. In addition, for mAs, the statistical results were between 175 and 300 mAs, with a mean of 233 mAs and a median of 230 mAs, resulting in a standard deviation of 38.5, which indicates that there is a clear difference in the amount of radiation used, but revolves around a value of 233. In general, standard deviations indicate the presence of variation in values, but it is not large, which means that there is a relative balance in the data.

The results of the one-way ANOVA tests, as presented in Tables 3 and 4, reveal a statistically significant impact of both exposure parameters: kVp and mAs, on the types of CT image distortion, with p-values < 0.001 for both, this indicates that variations in kVp and mAs are strongly associated with the presence and severity of different artifact types in CT images. Further, the between-group variances were notably higher than within-group variances, confirming that different distortion categories correspond to distinct exposure parameter settings. Therefore, these outcomes confirm the critical role of carefully selecting values: kVp and mAs, to minimize image artifacts and improve diagnostic accuracy.

The results demonstrate the impact of exposure settings on radiographic image quality; therefore, artificial intelligence solutions will be discussed as a means of reducing defects and improving diagnostic accuracy, which this study results demonstrated a clear relationship between CT exposure parameters: kVp and mAs, and the degree of artifacts in the resulting images, such as noise, metal artifacts, and partial volume effects. These artifacts negatively impact diagnostic accuracy and can lead to errors in pathological diagnosis and treatment plans.

In this context, deep learning algorithms and artificial neural networks can automatically recognize different types of artifacts with high accuracy, helping to classify them and reduce their impact on the final image. AI-powered image reconstruction techniques also improve image quality even when using low doses of kVp and mAs, achieving an important balance between reducing patient radiation exposure and maintaining diagnostic quality.

Furthermore, AI can predict image quality based on pre-scan parameters, providing automatic recommendations for adjusting settings to reduce the likelihood of artifacts, thereby reducing the need for re-scans, saving time and effort for clinicians, and supporting more objective and accurate clinical decisions. Therefore, incorporating AI technologies into CT imaging protocols enhances diagnostic quality and improves the patient experience by reducing radiation doses and reducing errors due to artifacts, which aligns with the study findings, which emphasize the need to review and get better exposure parameters in conjunction with modern AI technologies.

Table 1: Clinical case data with imaging parameters and types of distortion in CT images.

Case No.	Age (Years)	Gender	kVp	mAs	Type of Distortion
1	23	Female	113	185	Noise
2	25	Male	115	190	Noise
3	32	Female	100	200	Beam Hardening
4	34	Male	102	205	Beam Hardening
5	36	Male	137	215	Partial Volume Effect
6	37	Male	107	275	Beam Hardening
7	38	Female	135	210	Partial Volume Effect
8	39	Female	105	280	Beam Hardening
9	40	Female	120	180	Noise
10	41	Male	122	175	Noise
11	42	Male	125	260	Metal Artifact
12	44	Female	127	265	Metal Artifact
13	45	Male	120	250	Motion Artifact
14	47	Female	118	255	Motion Artifact
15	50	Male	115	240	Motion Artifact
16	52	Female	117	235	Motion Artifact
17	55	Female	110	300	Metal Artifact
18	56	Male	112	295	Metal Artifact
19	67	Female	132	225	Partial Volume Effect
20	68	Male	130	220	Partial Volume Effect

Table 2: Descriptive analysis of patient age and CT imaging parameters: kVp and mAs.

Variable	Minimum	Maximum	Mean	Median	Standard Deviation
Age (Years)	23	68	43.55	41.5	11.98
kVp	100	137	118.1	117.5	10.66
mAs	175	300	233	230	38.5

Table 3: One-way ANOVA test for the impact of kVp values on CT image distortion types.

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-value	P-value	F-critical
Between Groups	1804.8	4	451.2	19.17	9.22×10^{-6}	3.06
Within Groups	353	15	23.53			
Total	2157.8	19				

Table 4: One-way ANOVA test for the impact of mAs values on CT image distortion types.

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-value	P-value	F-critical
Between Groups	20770	4	5192.5	10.53	2.88×10^{-4}	3.06
Within Groups	7400	15	493.33			
Total	28170	19				

7. Conclusion
Through this research study, it became clear that the exposure parameters kVp and mAs used in the CT machine play an important role in obtaining certain percentages of image distortion, as the statistical results of the 20 samples obtained from Al-Sadr Educational Hospital in Najaf, showed a close relationship between these parameters and image distortion, and thus obtaining low accuracy in diagnosis, which leads to affecting the health of the reviewers due to errors resulting from misdiagnosis. From all of this, it is clear that it is necessary to review the protocols followed in imaging by CT to produce a high-resolution radiological image and maintain a low radiation dose, as well as enhance the role of AI in treating distortion in radiological images to avoid diagnostic errors.

Conflict of Interest
Not available.

Financial Support
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