Image Learning And Correction As A Means Of Evaluating And Fault Finding Computer Scanner Image Artefact

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Abstract. The concept of image reconstruction modelling in both the industry and academia has led to the investigation of different artefacts found in the medical fraternity, specifically in radiology and x-ray. This concept is aimed at optimising the efficiency of fault-finding image artefacts in the CT scanner. It is for such reasons, that an automated artefact detection model with capabilities for artefact image restoration and solution prediction model needs to be investigated, developed, and implemented to evaluate the feasibility and reliability of such a system in a live environment setup for service engineers and specialist alike. During the image acquisition process, images were taken from Toshiba medical equipment for image processing and machine learning purposes. The data collected contains 100 images in the dataset comprising of 50 ring and metal artefact images for data testing with 19 iterations. Training of the model is created to allow the model to learn by identifying the different features. This paper demonstrates the consistency of the model in distinguishing between the ring and the metal artefact from a “normal” scanned image. However, the model accuracy inconsistency and required data augmentation to stabilise the system, hence the need for algorithm optimization to accurately detect and distinguish the artefacts despite the image sample number.

Keywords: Artefact, Image Processing, CT scan, Artificial Intelligence, OpenCV, Machine Learning.

Introduction

Image Processing (IP) has become one of the most vivid research areas in Computer Vision, especially in Medical Imaging (MI) sector. Medical imaging system in certain instances makes use of captured images for diagnostic and monitoring purposes. Medical imaging system modalities include x-rays scanners, Magnetic Resonate Imaging (MRI) scanners, Virtual Surgical Planning (VSP) systems, and Optical Coherence Tomography (OCT) amongst a wider range of equipment used to assess the conditions of organs or tissue and monitor a patient over time for diagnostic and treatment procedures.

Computer-Aided Diagnostic (CAD) schemes and Artificial Intelligence (AI) show potential in providing multiple industries that are image processing dependent with “visual aid” and increase confidence in accepting computer-aided-cued results in the decision making [1].
Medical imaging systems comprises of several developed techniques, and each technique has different risks and benefits. The risks associated with medical imaging are similar risks that are found in every image processing-based application such as Photoshop and Google Maps, just to name a couple of the popular ones [2]. However, in the context of computer vision, Computer Tomography (CT) and MRI scanners are dominant applications in medical imaging because of their high resolution, good signal-to-noise ratio, and manipulation properties, as well as having some knowledge about the entire systems. Furthermore, despite the risks associated with image processing, medical imaging has been seen to have major risks such as the visualisation that details the image data analysis and exploration for research applications. The concept of image reconstruction and modelling is introduced to allow for instant processing of 2D signals to create 3D images and colouring to reduce data collection time and image interpretation [3]. Additionally, digital image processing software is designed to automatically identify and analyse what might not be apparent to the human eye.

This paper focuses on implementing image correction measures for a CT scanner to affect the outcome of an image and to fault find image distortions utilising machine learning applications. The final objective of this study is, therefore, to; 1) To present a method for artefact detection and reconstruction; 2) To develop a method that can distinguish between metal and ring artefacts and provide a possible solution matrix using machine learning techniques. To summarise, this article proposes an automated model for artefact analysis, detection, and provision of possible solutions.

The remainder of this paper is as follows. Section 2 provides the problem statement elaborating on the research question. Section 3 provides a discussion on the literature around medical devices, corrective techniques, and the application of CAD in the medical environment. Section 4 outlines the systems modelling technique utilising image processing and machine learning techniques for data training, data identification, data training, and provision of a possible solution. The results are outlined in Section 5 with the paper concluded in Section 6.

**Problem statement**

Currently, there are standard troubleshooting procedures that are used in practice to overcome image artefacts in the CT scanners. However, troubleshooting may still yield negative results, and this may be due to the evaluation or nonuniform fault-finding technique since the troubleshooting exercise is manufacture-specific. However, the said fault-finding techniques can be time-consuming and costly, which in turn is a setback for radiographers, doctors, and even patients.

It is for such reasons, that an automated artefact detection model with capabilities for artefact image restoration and solution prediction model needs to be investigated, developed, and implemented to evaluate the feasibility and reliability of such a system in a live environment setup for technical representatives and service engineers.

**Literature review**

MI systems have made the highest advancements in medical technology both academically and for medical research purposes. Dougherty et al. [4] present the medical imaging system for constructing an image in response to signals from diverse types of objects namely bodies and phantoms. Additionally, Dougherty highlights that medical imaging systems can be classified according to the radiation, and academic field of use. Dougherty further investigate the properties of whether the
images are formed directly or indirectly. A Computer Tomography (CT) scanner is a diagnostic imaging procedure that uses x-rays to build cross-sectional images of the body [5].

Each time the x-ray source completes one full rotation, the CT computer uses sophisticated mathematical techniques to construct a 2D image slice of the patient or object, producing signals that are processed by the machine’s reconstruction component to generate cross-sectional images (slices) of the patient or object. These slices contain more detailed information than conventional x-rays. Once several successive slices are collected by the CT scanner, they are digitally stacked to form a final three-dimensional image of the patient that allows for easier identification and location of basic structures as well as possible tumors or abnormalities.

Furthermore, equipment such as Magnetic Resonance Imaging (MRI) which is a medical imaging technique that is used in radiology to form pictures of the anatomy and the physiological processes of the body [6] is currently in use. MRI scanners use strong magnetic fields, magnetic field gradients, and radio waves to generate images of organs in the body. MRIs are deemed as one of the most important non-invasive imaging techniques in medicine not only due to the non-invasiveness of the method but due to its richness of the attainable tissue contrast [7].

**Historical background on CT scanners**

CT scanners are ideally set to be established in 1971, citing Hounsfield and Ambrose positioning a patient inside a new machine in the basement of the hospital. However, the argument has been around for decades that Damadians is the first author/developer of the CT scanner technology in 1977 [8]. This is contrary accordingly to different authors. It is, however, agreed that the first functionally developed CT scanners made use of pencil-like beam X-ray sources located across from a single x-ray detector.

The first-generation scanners were published in the mid-1970s, and it was translated linearly across the field of view and was projected as a series of parallel beams. Figure 1 depicts first-generation CT scanners transmitting a single-shaped beam.

![First-generation CT scanners single pencil beam-shaped transmission](http://www.webology.org)
Figure 1 depicts the first-generation CT scanner. The source in the translation model is placed parallel to the beam-shaped transmission. For the additional test model, the source is rotated 1o to evaluate the best optimal model.

**Review on correction techniques used for CT image artefacts**

The induced artefact in many documented field experiences ring artefacts caused by degraded electronics. As a result of the degraded electronics, the avoidance and software are implemented for the selection of the correct scan details and protocols of the full system calibration and knowledge of anatomy.

In retrospect, Eldib et al. [8] proposed a corrective method for a cone-beam CT by correcting the defective pixels whose values are close to zero or saturated in a projection domain. Subsequently, Salplachta et al. [9] introduce a new ring artefact reduction procedure that combines several ideas from existing methods into one complex and robust approach.

**Review on image recognition and learning techniques for medical image systems**

There are several types of conventional techniques used to identify and learn about CT images, with the most obvious one being visible to the human eye. However, these methods are aligned with certain types of artefacts. Some artefacts are new and are mainly caused by faulty or degrading electronic components and external factors like the room temperature and dirt, just to name a couple.

In retrospect for pattern recognition, machine learning techniques have become instrumental in the development of CAD systems. Duda et al [11] state that pattern recognition is the act of extracting features from some objects in raw data and making a decision based on the classifier output such as classifying each object into one of the possible categories of various patterns. However, the basic concept of introducing CAD systems in medicine was proposed to provide a computer output as a second opinion to assist radiologists in interpreting images, so that the accuracy and consistency of radiological diagnosis could be improved, also that the image reading time could be reduced.

**Methodology**

The system development model comprises of data acquisition, data testing, data modelling, and the application algorithm for data training and provision of a possible solution. The data is collected by taking pictures of different artefacts namely ring, and metal artefact and convert them to a listed dataset. During the image acquisition process, the images are taken from Toshiba medical equipment and are saved them into a folder, which is then converted into a listed dataset. Figure 2 depicts the initial images taken for image processing and machine learning purposes.

However, the two phantoms were used to evaluate the artefact by physically comparing each image with an artefact against an image without an artefact. Additionally, after the data was collected, a model was developed to create an enabling environment for data training and to allow the same data to be fitted into the same data training model for evaluation and model training purposes. Figure 2 further depicts the ring and metal artefact that are investigated in this article.
Figure 2. Image sample of both a) ring artefact; b) metal artefact taken from Toshiba equipment.

Figure 2 depicts the image samples obtained from a Toshiba CT scanner. Each image represents a type of an artefact in this instance a) ring artefact; b) metal artefact. Furthermore, Figure 2 depicts the images already placed in the model before applying the learning algorithm to the model. These images are a representation of an image with either a ring artefact or metal artefact.

System modelling development procedure and tools

In modelling of this system, the following libraries and algorithms were used:

- Tensor flow TM – this software is utilised as a machine learning software on PyCharm IDE
- OpenCV – for image processing and detection of features
- Keras library – is a library interface for Tensor flow TM and is utilised as a supporting library for machine vision

Furthermore, these algorithms utilises a CUDA-based Graphical Processing Unit (GPU) that allows for parallel computing provided by the GPU. The system model setup was then outlined as indicated in Figure 3.

- Image data collection and preparation
- Dataset creation and data model training
- Image testing
- Model evaluation
Figure 3. Model setup framework.

Figure 3 depicts the model task overview outlining the model setup framework. This setup is consisting of four key components namely 1) collect and prepare data; 2) Create and train the model; 3) Evaluate the model using unknown and known data; 4) test the model.

- Collect and prepare presents the start of the project and how the data is collected for the model. The data is collected by scanning an image with Toshiba equipment and manually checking the images against the scanner datasheet to identify the type of artefact. Upon noting the type of an artefact, a folder is created and images are multiplied to reach 50 image samples, then copied into a listed folder per artefact type i.e. metal artefact. However, no scientific model or principle was utilised for image sampling number per dataset, and it was the prerogative of the researcher to estimate the image sample number. It is noted that the sample number might affect the results output.
- A train and test model were created utilising the feature learning model that relies on the following: a) input data; b) convolution; c) pooling and classification model. The system is trained by inputting a dataset into the model and the 19 iterations are executed in PyCharm IDE for data training. Upon, the completion of the iterations, an unknown dataset with the same image dataset is inputted and the output is observed.
- The input of unknown image dataset is to evaluate the accuracy of the model and the results are observed and evaluated against the initial dataset. Each dataset has notes aligned with it containing possible solutions.
- The sample code below depicts the directory for datasets. Furthermore, Figure 4 depicts the data structure of the datasets and modeling assets directory.
Figure 4 depicts the data modelling structure for locating the datasets for both the training data and the validation data. Upon locating the data, the feature learning model is applied to the data by first resizing the image’s width and height before the convolution is applied. The application of convolution is to differentiate the two artefacts based on their features. The system is trained by inputting a labeled dataset into the model and testing is performed by inputting an unknown dataset into the model and the output results are evaluated against a set of reconstructed image datasets and solutions. The system is trained with 19 iterations using machine learning techniques. Upon the completion of the iteration, the model is tested and evaluated against the unknown data to test for accuracy. The system model is then evaluated on the unknown data and this data is then used to determine the artefact type and possible solution.

Additionally, Figure 5 further explains the “collect and prepare data” with references to the image sizes. The image size used was 512x512 pixels. Additionally, in most CT scanners, the gantry’s bore size used in simulations of radiation therapy is bigger to accommodate situations in which the overall diameter of imaging volume is large owing to immobilisation devices [12]. However, this resonates with the physical development of the CT scanner, while this article focuses on reconstructing the captured images in a form of a dataset.
Figures 5 a) and b) depict the original captured image artefacts for both metal and ring artefacts. Since these images are taken from the same source, they are manually sorted by placing them into a master folder and a dataset is created for both the metal and ring artefact and is labeled as such per artefact.

Each data collected contains 100 images in the dataset that is organised as follows:
• Ring artefact - training 50 images for data testing with 19 iterations
• Metal artefact - training 50 images for data testing with 19 iterations

The training of the model is created to allow the model to learn by identifying the different features as outlined in Figures 6 a) and b) for both metal and ring artefacts.
Figures 6 a) and b) depicts the test application of the datasets in the model. Figures 6a) and b) depict both the metal and ring artefact dataset that is placed in the model for training and validation. Figures 6 c) and d) further present the difference between the original image and feature detected image for both ring and metal artefact. This is pivotal as the recognition is depended on these features for accuracy testing. This model is fully automated and once the input image or dataset is applied into the model, the model analyses the image and provides the output as per the defined procedure above.

Figure 7. Model flow diagram.

Figure 7 present the algorithm flow diagram. The two datasets (ring and metal artefact) are loaded into the model. The data is then augmented to increase the training datasets. This is pivotal because it has been seen that the fewer the images in the dataset, the higher the possibilities of inaccuracy.
This was conducted in a trial-and-error method and no scientific approach was applied as machine learning prediction depends primarily on the dataset dimensions.

The dataset data parameter generation is then applied as follows:

- **rescale** — Each digital image is created by a pixel with a value between 0 and 255. 0 in black, 255 in white. So, the rescale of the scaled array of the original image pixel values should be between [0,1] which makes the images contribute more equally to the overall loss. Otherwise, higher pixel range image results in greater loss and a lower learning rate should be used, lower pixel range image would require a higher learning rate.
- **shear_range** — The shape of the image is the transformation of the shear range. Its function is to fix one axis and stretches the image at a certain angle known as the angle of the shear.
- **zoom_range** — the image is enlarged by a zoom of less than 1.0. and when the image is more than 1.0 then the image zoomed out.
- **horizontal_flip** — some images are then flipped horizontally at random to have a full view of the images in both the horizontal and vertical positions.

Upon successful execution of this process, CNN architecture is applied on a model, however, the CNN model needs to adhere to the following process as follows:

- Always begin with a lower filter value such as 32 and begin to increase it layer-wise.
- Construct the model with a layer of Conv2D followed by a layer of Max Pooling.
- The kernel_size is preferred to be an odd number like 3x3.
- Relu was used for activating the function
- Input_shape takes in image width & height with the last dimension as colour channel.
- Flattening the input after CNN layers and adding ANN layers.
- Use activation function as soft max for the last layer if the problem is more than 2 classes, define units as the total number of classes and use sigmoid for binary classification and set the unit to 1.

A 22-layer 2D CNN design was developed which consist of five 2D convolution layer, with the second layer comprising of 32 filters and the third layer of 64-layer filters all with a kernel size of 3x3. Each convolution (Conv) layer is followed by a Re Lu activation layer and it ends with max-pooling (MAXPOOL) layer with a stride of 2. The feature extraction block consists of CONV-Re Lu-MAXPOOL modules and the output from the extraction block is then flattened and passed to a fully connected layer with 475,746 parameters. In the early days of image processing development, linear filters were used as the primary tools for image enhancement and restoration. However, due to the advancements in technology, other algorithms such as supervised learning multi-class classification logistic regression algorithm and linear regression algorithm are currently in use in the market. In this article, the logistic regression algorithm is utilised citing the difference between the two algorithms as outlined in Table 1.

### Table 1. Difference between linear and logistic regression algorithms in machine learning

<table>
<thead>
<tr>
<th>Linear regression algorithm</th>
<th>Logistic regression algorithm</th>
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2822 http://www.webology.org
Predicts the continuous dependent variable using a given set of independent variables
Solves regression problems
Predicts the value of continuous variables
Easily predict the output
The least-square estimation method is used for the estimation of accuracy
Continuous value

Predicts the categorical dependent variable using a given set of independent variables
Solves classification problems
Predict the values of categorical variables
Find the S-curve by which we can classify the samples
The maximum likelihood estimation method is used for the estimation of accuracy
Categorical value i.e., 0 or 1

Additionally, the correction and origin are depicted in both medical and industry. However, the use of logistic regression is aligned with the proposition for addressing the artefacts problem that is seen in medical facilities. Additionally, the brightness of an image is altered with distance in either the horizontal or vertical direction of the image by checking the high spatial frequency. When the brightness changes slowly or at a constant rate, the image is said to have a low spatial frequency. Spatial frequency filtering can alter an image by sharpening, smoothing, blurring, and applying noise reduction and feature extraction.

Results

Based on the model output sequencing and accuracy testing. The accuracy testing was based on two image datasets with 50 sample images per dataset. This test was evaluated utilising an unknown image dataset that was not part of trained data. This allowed for the model to predict the model accuracy with a dataset of 50 images each. However, to optimally get conclusive results a weight or benchmark of 80% was added and the model output was supposed to obtain this threshold with the given datasets.
Figure 8. a) Model data loss; b) Model accuracy.

However, the model required data augmentation to provide conclusive results. As this was not part of the study, the results were then based on the 50 images per dataset. Figure 8 a) depicts the model results for data loss or inaccuracy for 35 epoch iterations. Figure 8 a) depicts that as the model epoch counts increase the data loss reduces and this is due to the number validation conducted, with data loss being 0.49 on the 24th epoch as compared to 0.70 on the 0th epoch test. Subsequently, in Figure 8 b), as the data model training increases, the model accuracy increases with the system producing 0.4 accuracy test at epoch 0 and 0.8 accuracy test and epoch 25. This incremental accuracy is due to multiple data training applications.

Conclusion

This paper observed the modelling of a system for the detection and identification of two kinds of artefacts mainly ring and metal artefact. However, using machine learning and image processing techniques such as Keras library and OpenCV the system was deemed efficient and effectiveness was measured against the accuracy results based on the number of image samples within the dataset. The results do prove that the system is efficient and effective in identifying the different artefacts based on the features. However, the accuracy of the model is deemed not as effective, hence the need for data augmentation is required. This thus concludes the study that the model’s accuracy is not 100% accurate, therefore an optimization algorithm needs to be added to the model for the model to provide over 80% accuracy despite the number of image samples. This algorithm optimization will provide the required enhancement that will augment the model’s accuracy by not only depending on the system features but rather the learning algorithm should be sufficient.

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References


