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Review

Preliminary Landscape Analysis of Deep Tomographic Imaging Patents

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Abstract: Over recent years, the importance of patent literature has become more recognized in the academic setting. In the context of artificial intelligence, deep learning, and data sciences, patents are relevant to not only industry but also academe and other communities. In this article, we focus on deep tomographic imaging and perform a preliminary landscape analysis of the related patent literature. Our search tool is *PatSeer*. Our patent bibliometric data is summarized in various figures and tables. In particular, we qualitatively analyze key deep tomographic patent literature.

Keywords: Artificial intelligence (AI), machine learning; deep learning; medical imaging; tomography; image reconstruction

1. Introduction

With the advances of artificial intelligence (AI), deep learning (DL) has emerged as a mainstream approach with successful applications in many areas. Since 2016, deep reconstruction or deep imaging methods have been actively developed, especially in the field of medical imaging [1-3]. Promising results on medical imaging are widely reported on diverse topics ranging from data acquisition and processing, image reconstruction and enhancement, to radiomics and health analytics, and more. Clearly, AI/DL is paving an exciting way to improve or innovate medical imaging devices, and diagnostic and therapeutic procedures. With rigorous and systematic assessment and regulation, AI imaging software and devices may assist or compete effectively with radiologists, eventually transforming the current model of medical and healthcare practice in various aspects.

According to a 2020 press release from the Yole Group (http://www.yole.fr/Artificial_Intelligence-Medical_Imaging_focus.aspx#.YVSUzprMKUk), "*AI has the potential to change all of our diagnostics and treatment procedures to enable more personalized and effective medicine.*" "*At Yole, we estimate the total market in 2025 for software generated revenues through the sale of AI tools will reach US$2.9 billion with a 36% CAGR (Compound Annual Growth Rate) between 2019 and 2025. These revenues can be shared between the main applications including improved image capture, noise reduction, image reconstruction, screening, diagnostic and treatment planning*."

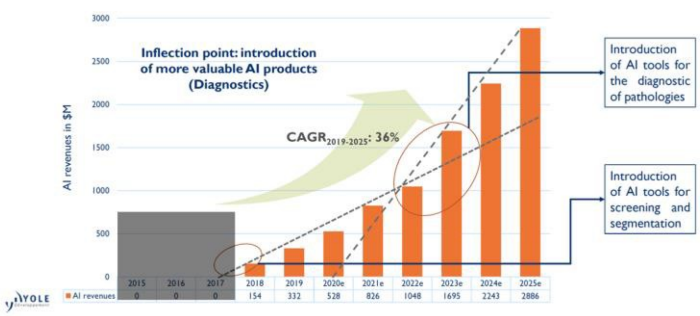

Figure 1. AI revenue of the medical imaging companies from 2015 to 2025 (adapted from www.yole.fr).

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Given the huge commercial potential of AI-based imaging technologies, intellectual property plays increasingly important roles in the imaging industry, research and user communities. In this context, for researchers and developers, patent landscape analysis and literature review are indispensable. To understand the landscape of AI-based deep tomographic imaging technologies that promise to be clinically relevant, we are motivated to survey relevant patent literature over the past decade or so. As used herein, "patent literature" includes issued patents and published patent applications (i.e., pre-grant patent application publications). As further used herein, "patent documents" include issued patents and pre-grant patent application publications ("PGPubs").

The rest of this paper is organized as follows. In the second section, we present our methodology. Our main patent search tool is *PatSeer [4]*. Our search strategy and analysis methods are described. In the third section, we present our *PatSeer* search results in various figures and tables. While the third section is largely data-driven, in the fourth section we analyze key deep tomographic patent documents aided by citation analysis. In the last section, we discuss relevant issues and conclude the paper.

2. Methodology

Over recent years, the importance of patent literature has become more recognized in the academic setting, as evidenced by the establishment of the National Academy of Inventors in 2010. In the context of artificial intelligence, deep learning, and data sciences, patents are relevant to not only industry but also academe and other communities. To perform our landscape analysis of the patent literature on deep tomographic imaging, we used the patent search and analysis tool *PatSeer*. We note that other patent search and analysis tools are available including, but not limited to, AcclaimIP (available from Anaqua), LexisNexis TotalPatent One®, etc.

Specifically, the tool we used is *PatSeer ProX*, developed by Gridlogics. *PatSeer ProX* includes big-data analytic methods and performs relatively fast through, in our opinion, a very user- friendly interface. We find that the search rules used by *PatSeer ProX* are like those used by Scopus (a curated abstract and citation database from Elsevier). According to the *PatSeer* website, the *PatSeer ProX* patent database covers more than 136-million patent publications, 96-million full-text records, and 10-million normalized companies and universities. Furthermore, *PatSeer* maintains a scalable big-data platform with AI-based semi-automated algorithms to process and analyze raw data from over 300 sources.

As an initial illustration, with the "deep learning" as the search phrase in the title, abstract and claim fields from Jan. 1, 2010 to the end of 2021 (*TAC:("deep learning") AND PBD:[2010-01-01 TO 2021-12-31]*), Figures 2 and 3 were generated in seconds.

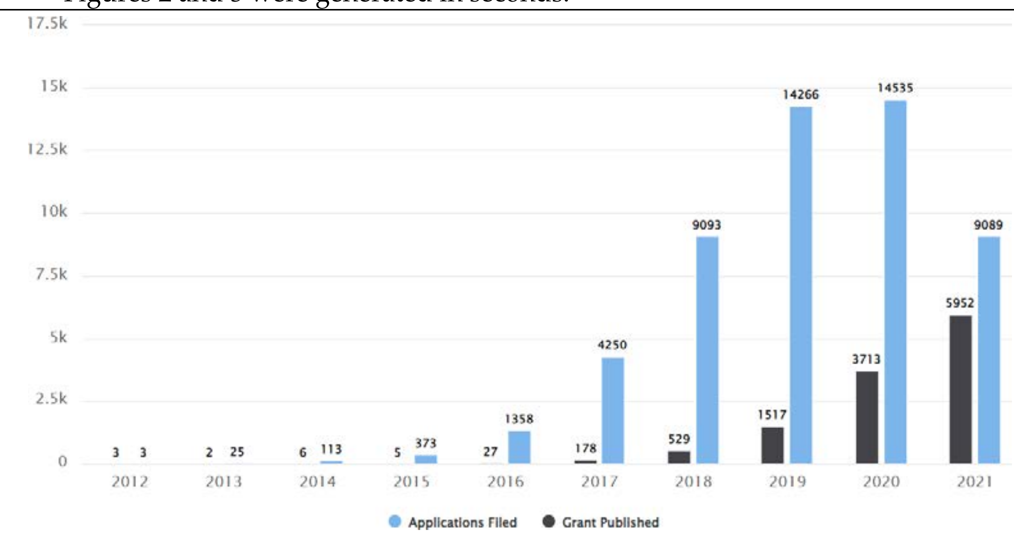

Figure 2. Patenting trend in the field of deep learning. The chart shows filing and grant data, with *the applications being plotted by filing date and the grants by publication date.*

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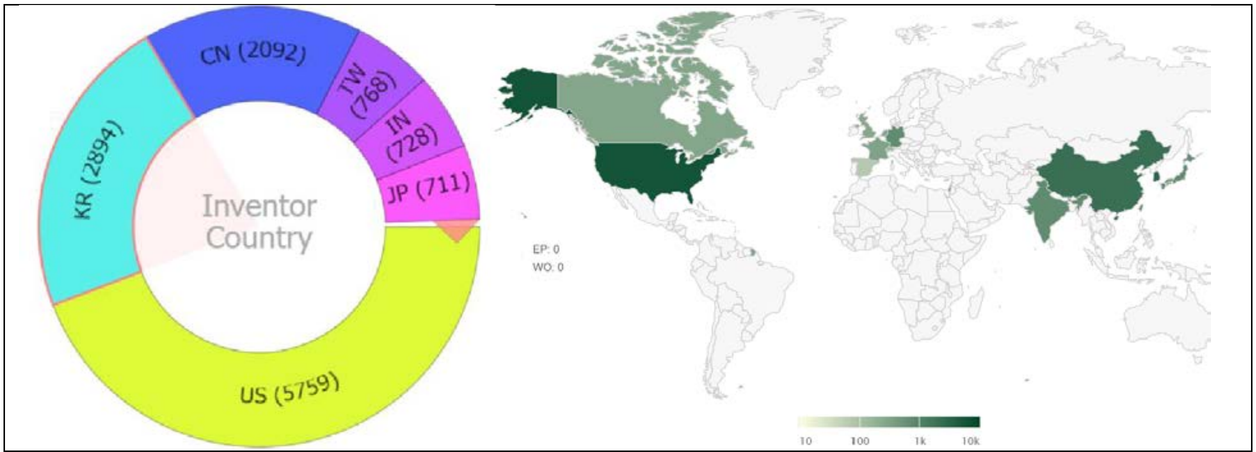

Figure 3. Distribution of inventors by country of residence. The left chart shows the number of records by the country of residence of inventors. The right chart shows the number of records by the country where the application was filed. Note that a record is included in each unique country (the same record may be repeatedly counted).

3. Visualization of Patents on Deep Tomographic Imaging

In this section, we focus on our patent search results on AI-based medical imaging techniques. Initially, we performed keyword-based searches in the title, abstract and claim fields but we obtained quite many irrelevant results. For example, the inclusion of claims may include some irrelevant results. For example, French PGPub FR2733596B1 [5] only mentions "Ultrasound" in the claims. As another example, International PGPub WO0124700A1 [6] is for fingerprint detection. As a result, our searches were limited to the title and abstract fields only. After further deliberation, we defined the following search expression: *TA:(("machine learning" or "deep learning" or "deep nets" or "neural network" or "deep network" or "deep neural network" or "artificial intelligence") and ((raw data process* or "k-space data" or "tomographic data" or "sinogram" or image reconstruct* or post-process*) or ("image quality" or "artifact reduction" or "low dose scan" or "fast scan" or "under sample" or "noise reduction")) and (medical imag* or tomograph* or "CT" or "computed tomography" or "PET" or "positron emission tomography" or "SPECT" or "single photon emission computed tomography" or "nuclear imaging" or "MRI" or magnetic resonance" or "Ultrasonography" or "ultrasound" or "optical coherence tomography" or "OCT") and not ("display apparatus" or assess*))*, where TA means in the title and abstract fields. Note that the filter function, *not ("display apparatus" or assess*)*, was empirically added to exclude irrelevant hits; for example, DE69031523D1 [7] matches the other parts of the overall expression but only describes a method to optimize a display window, and US8086007B2 [8] describes an image quality assessment method. In total, this search yielded 757 records.

Figure 4 summarizes the numbers of patents per application year grouped by the original assignee. Figure 5 lists the top 10 most cited patents in this domain. A few examples are described here. PGPub US20180018757A1 describes a method to transform low-quality projection data into high quality projection data using machine learning models. International PGPub WO2017223560A1 [9] describes machine learning-based tomographic/tomosynthetic techniques that use a neural network that includes more than three layers and can be applied to either raw data or initial image domains. PGPub US2020034998A1 [10] is an example of deep learning for MRI imaging, where a neural network model is used with data consistency.

To assess the quality of an issued patent or published patent application quantitatively, *PatSeer* provides a 360° Quality metric, which is a weighted average of 4 contributing scores. The contributing scores include Citation Quality (CQ), Market Quality (MQ), Legal Quality (LQ) and Document Quality (DQ) [4]. CQ considers the number, recency and type of forward citations of a patent document. MQ is based on the patent family's global market coverage. LQ reflects how aggressive the company protects the patent family. DQ measures the intrinsic quality of a patent based on its structural elements. Then, the portfolio value index is defined as the sum of the 360 Quality scores of all the patent families present in a portfolio, which, according to Gridlogics, is roughly proportional to the overall realizable value of the portfolio.

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Figure 4. Innovation timeline by original assignee versus application date, where innovation intensity is shown by number of assigned patent applications per assignee per year.

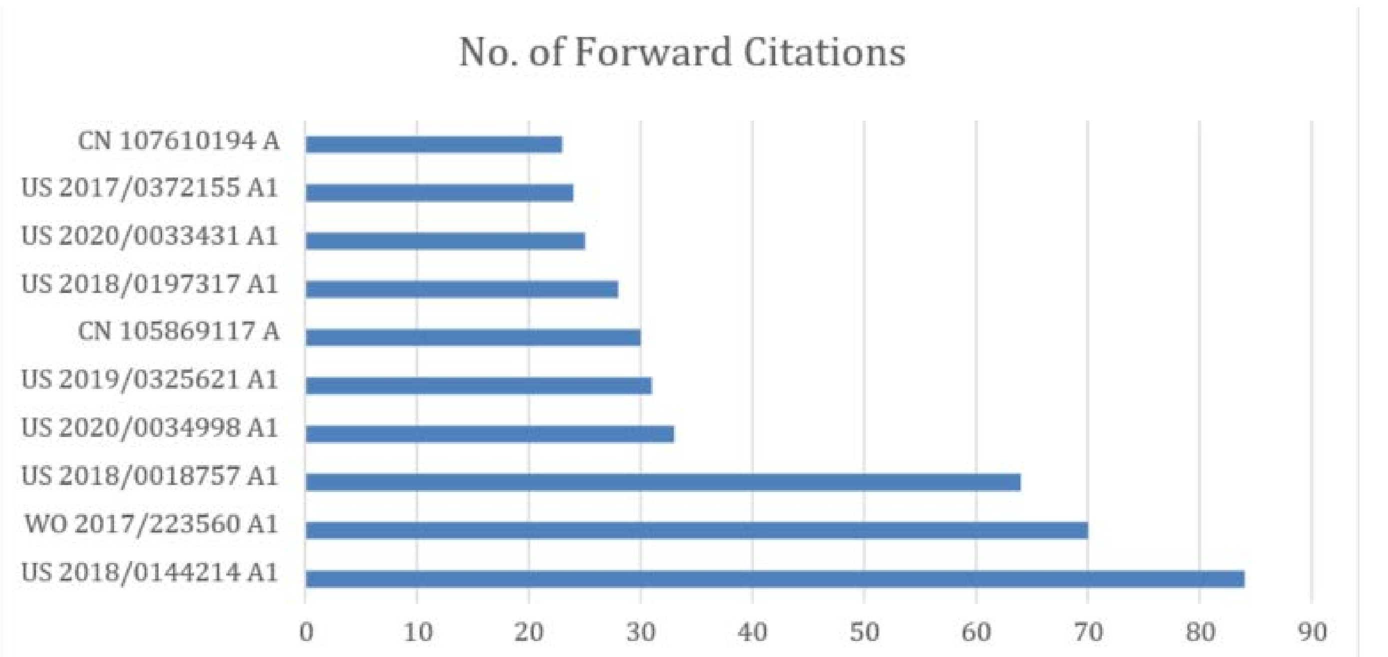

Figure 5. Top 10 most cited issued patents and PGPubs in the domain of interest.

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Figure 6 shows the most valuable portfolios, according to the *PatSeer* Quality metric. Among them, Generic Electric Co, Canon Inc and Siemens AG hold the most valuable portfolios as industry leaders, while Rensselaer Polytechnic Institute (RPI), Zhengzhou University and Stanford University are the academic leaders.

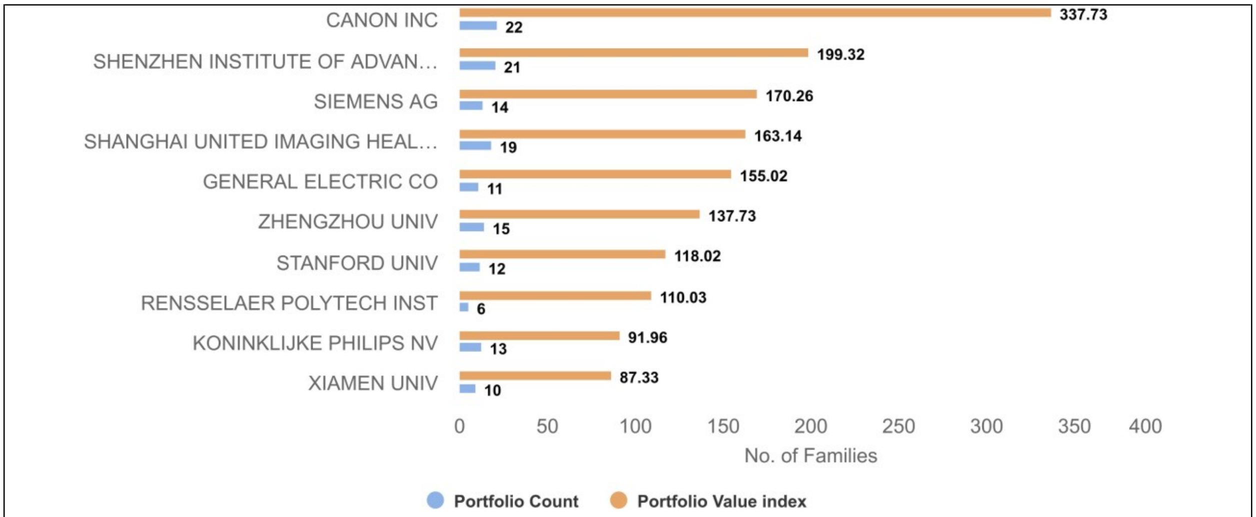

Figure 6. Most valuable portfolios (benchmarked by PatSeer's 360⁰ score) showing top players with the highest portfolio value index.

4. Analysis of Patent Literature for Deep Tomographic Imaging

We work in the medical imaging field with diverse interests but with an emphasis on CT. Given the broad view presented in the preceding section, in this section we analyze further deep CT reconstruction patent literature and other related technologies. This analysis provides a unique perspective that will help us plan future research and development activities. In the following sub-sections, we analyze patent literature based on specific applications and select representative patent documents for analysis. Tables 1-3 list related patent documents and further include brief comments.

4.1. Tomographic Image Reconstruction

Deep learning has significant implications for tomographic image reconstruction, as first described in our perspective paper on deep imaging [1]. Our perspective paper presents three specific examples with simulation results. When a dataset or an image is truncated, distorted or otherwise compromised, for example, in the cases of limited angle, few-view, local reconstruction, metal artifact reduction, beam-hardening correction, scatter suppression, and motion compensation, a synergistic combination of conventional tomographic methods and deep learning-based imaging may enhance image quality and diagnostic performance.

An international patent application (PGPub WO2017223560A1) [9] was filed with a priority date of June 24, 2016, describing tomographic image reconstruction systems and methods using deep learning techniques. This PGPub discloses a general framework for image reconstruction from raw data or a reconstructed intermediate image with the machine learning approach, suggesting a potential for deep tomographic reconstruction to surpass classic reconstruction algorithms.

Another published international patent application (PGPub WO2019074879A1) [11] is directed to image reconstruction with machine learning. The approach relates to the training of a machine learning algorithm for image generation and use of such a trained algorithm for image generation. Training the machine learning algorithm may involve using multiple images produced from a single set of tomographic projections or images. The trained machine learning algorithm may be used to generate a final image corresponding to a computationally intensive algorithm from an input image generated using a less computationally intensive algorithm. Issued patent US10475214B2 [12] uses machine learning to solve large-scale, space-variant tomographic reconstruction and correction problems. International PGPub WO2018126396A1

[13] presents deep learning-based correction and estimation of raw data for tomographic reconstruction.

International PGPub WO2019060843A1 [14] discloses an image reconstruction method using a machine learning regularizer. Specifically, an iterative reconstruction technique can incorporate a machine learning model as a regularization filter for the image reconstruction. International PGPub WO2018236748A1 [15] describes a deep learning-assisted image reconstruction scheme for tomographic imaging. The method reconstructs an image by performing an iterative reconstruction process to produce a plurality of intermediate images. The method further includes transforming at least one selected intermediate image from the plurality of intermediate images using a quasi-projection operator, which includes a deep-learning model configured to map at least one selected intermediate image to at least one regularized intermediate image.

PGPub US2018/0018757A1 [16] discloses a technique for improving projection data via machine learning. The method transforms low-quality projection data into higher quality projection data, and reconstructs high-quality tomographic images from the improved projection images. The machine learning model is trained with matched pairs of projection data; namely, lower–quality (lower-dose) projection data is paired with the corresponding higher-quality (higher-dose) projection data. After the training, the machine learning model can map lower- quality (lower-dose) data images to higher-quality (higher-dose) images. PGPub US2020311878A1 [17] describes an apparatus and method for image reconstruction using feature-aware deep learning. The neural network is trained to perform feature-aware reconstruction using a training dataset in which the target data has a spatially dependent degree of denoising and artifact reduction based on the features represented in the images.

The last technology we comment on is virtual monochromatic CT image reconstruction. International PGPub WO2019067524A1 [18] discloses processing current-integrating data and images via machine learning to produce virtual monochromatic images. The neural network is configured to learn a nonlinear function from a training dataset to map a CT image reconstructed from a single spectral current-integrating projection dataset to virtual monochromatic projections at a pre-specified energy level. The technique realizes monochromatic CT imaging and overcomes the beam hardening problem. PGPub

US2020196973A1 [19] discloses an apparatus and method for dual-energy CT image reconstruction using sparse kVp-switching and deep learning. The deep network reduces artifacts in CT images aided by complementary sparse-view projections generated from a sparse kilo-volt peak (kVp)-switching CT scan. The deep network is trained on input images that include artifacts and target images with little or no artifacts. Another deep network can be trained to perform image-domain material decomposition of the artifact-mitigated images.

4.2. Artifact Reduction

Metal artifact reduction is one of the remaining problems in the CT field. European PGPub EP3743889A1 [20] discloses using deep learning to reduce metal artifacts. The neural network is trained to extract a metal artifact affected residual image and generate a new image by subtracting the estimated metal artifacts from the input image. A relatively high number of patent documents target the same problem. Figure 8 lists some of them, ordered according to the number of forward citations.

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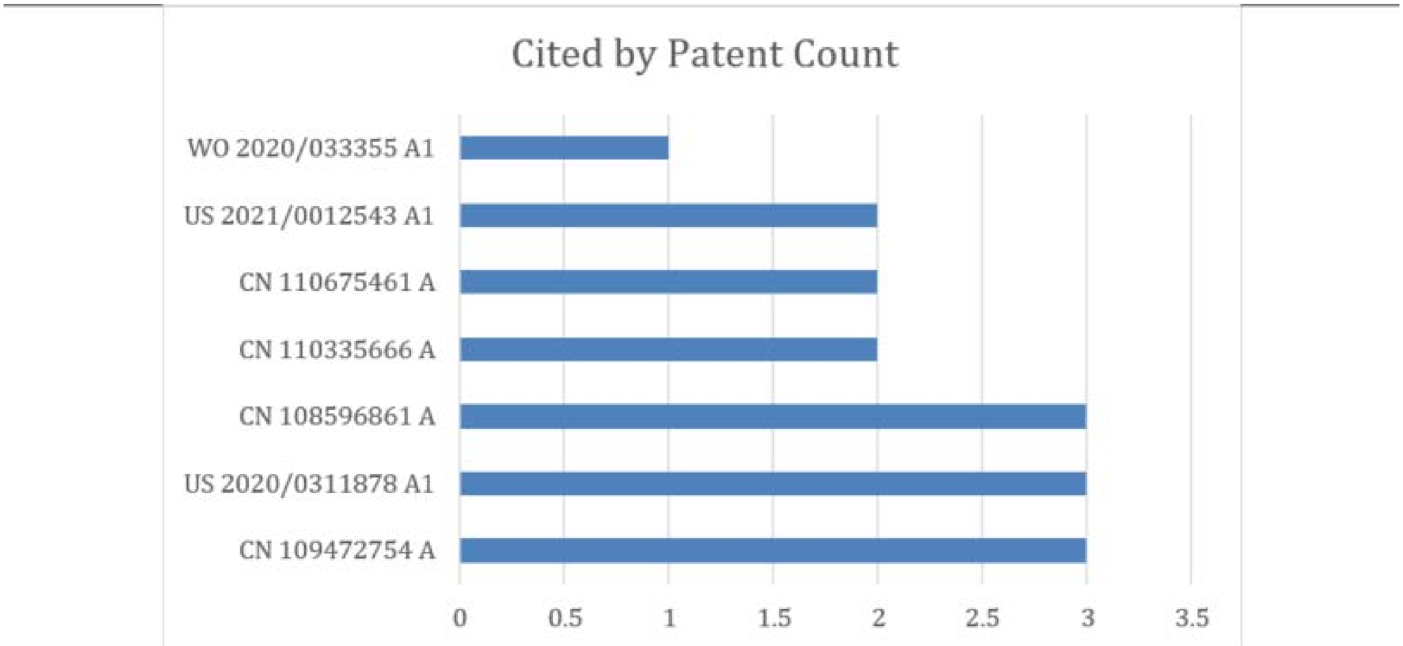

Figure 8. Most often cited patent documents related to CT metal artifact reduction, ranked by the number of forward citations.

The German PGPub DE102017219307B4, and Chinese PGPub CN109727203B [21, 22] describe a system and method for compensating motion artifacts via machine learning. The technology relates to a method for automatic compensation of motion artifacts in a medical image acquisition process. The technology further relates to a method for automatic identification of motion artifacts, and includes a compensation unit, a learning device, and a device for controlling a medical imaging system. A number of patent documents target this problem, as shown in Figure 9, ranked according to the number of forward citations.

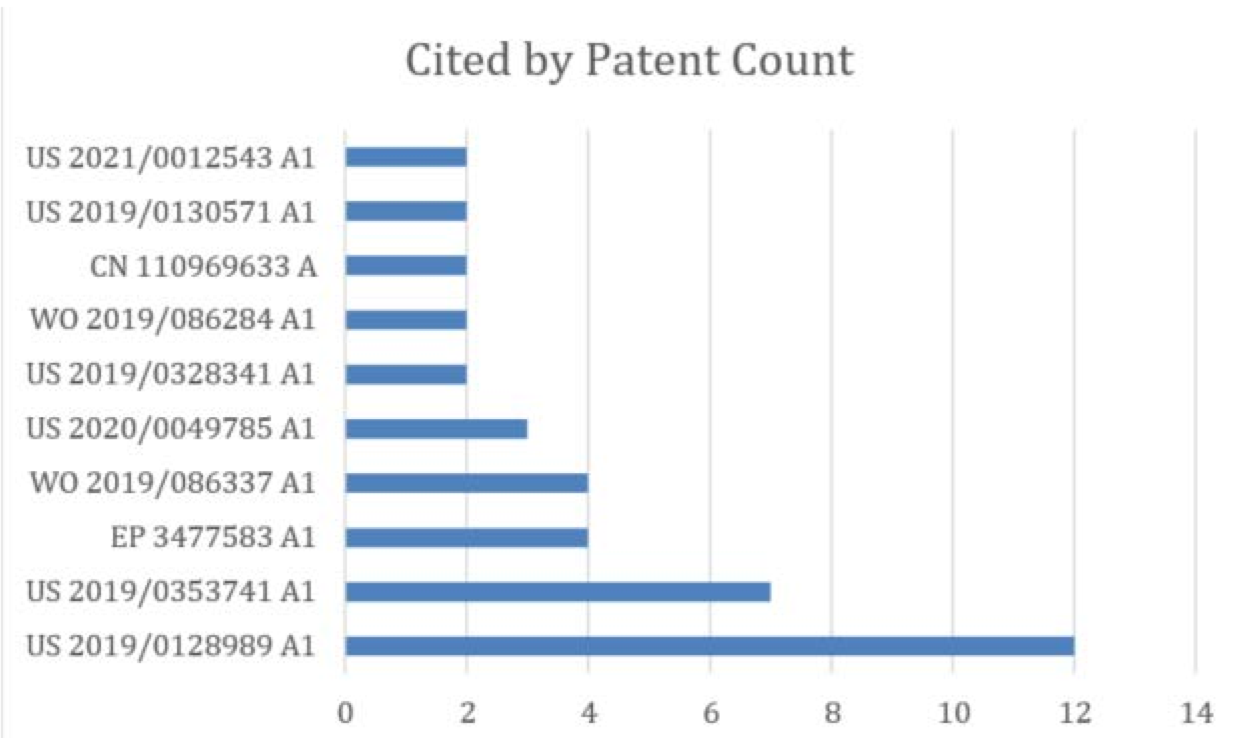

Figure 9. Most cited patent documents on CT motion artifact reduction, ranked by the number of forward citations.

The Japanese PGPub (JP2020534929A) [23] presents a deep learning-based scattering correction for x-ray imaging. A neural network is trained with imaging data generated in a Monte Carlo simulation. This includes

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simulations of at least one scattering mechanism that transforms CT data into scattering estimates in the projected space or converts uncorrected CT images into scattering estimates in the image space. After CT data are corrected to remove scatters in the projection space, the image reconstruction is performed to generate a scattering-corrected CT image. Scatter correction is also important for PET imaging. A number of patent documents exist related to deep learning-based scatter correction for either CT or PET, as shown in Figure 10.

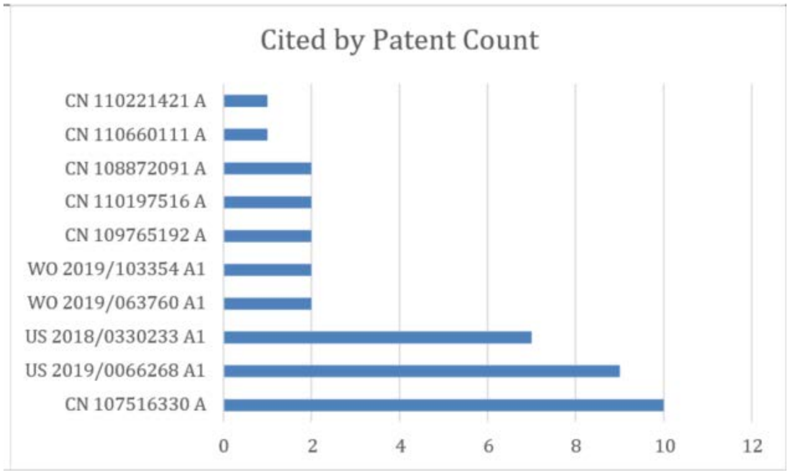

Figure 10. Most cited patent documents on CT/PET scattering correction, ranked by the number of forward citations.

4.3. Image Analysis, Radiomics and Rawdiomics

International PGPub WO2018232388A1 [24] uses neural networks to integrate tomographic image reconstruction and radiomic analysis. CT screening, diagnosis or image analysis tasks are often performed with separate neural networks and algorithms. Integrating these elements into an end-to-end workflow may streamline the whole process and optimize the task-specific performance. As we know, while deep reconstruction is for image formation from raw data, image analysis or radiomics is for image analysis. Thus, the claimed integration of image reconstruction and image analysis is referred to as "rawdiomics", where "rawd" means raw data, and "i" indicates images or informatics. International PGPub WO2018/220089A1 [25] applies machine learning to raw medical imaging data analysis for clinical decision support. The techniques are intended for medical diagnosis from raw imaging data generated by a medical imaging machine as opposed to a medical diagnosis of a medical image conventionally reconstructed from raw data.

Table 1. Representative Patent Literature for Image Reconstruction using AI Technology

No	Title	Comments	Owner	Priority Date
WO2017223560A1	Tomographic image reconstruction via machine learning	A machine learning method is proposed to achieve an improved tomographic image from raw data, processed data, or a reconstructed intermediate image.	RPI	06-24-16
WO2018126396A1	Deep learning based estimation of data for use in tomographic reconstruction	Trained neural network is used to estimate various types of missing projection data.	GE	01-05-17
US2018197317A1	Deep learning based acceleration for iterative tomographic reconstruction	A deep learning technique is used to accelerate iterative reconstruction of images.	GE	01-06-17
US2019102916A1	Systems and methods for deep learning-based image reconstruction	A method includes acquiring a set of imaging projections data, identifying a voxel to be reconstructed, receiving a trained regression model, and reconstructing the voxel.	GE	09-29-17
US2021074033A1	Deep learning-based data rescue in emission tomography medical imaging	An emission image is generated from poor quality emission data. A machine-learned model is used to recover information related to the data.	Siemens	09-09-19
US2017372193A1	Image correction using a deep generative machine-learning model	A deep-learnt generative model is used as a regularizer in an inverse solution with a physics model of the degradation behavior of the imaging system. The generative model is trained from good images, so difficulty gathering problem-specific training data may be avoided or reduced.	Siemens	06-23-16

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US2020311490A1	Apparatus and method for sinogram restoration in computed tomography (CT) using adaptive filtering with deep learning (DL)	A method is proposed to reduce the noise in medical imaging by training a deep learning (DL) network to select the optimal parameters for a convolution kernel of an adaptive filter that is applied in the data domain. The input data can be sinograms generated by a low-dose CT scan, and the target data generated by a high-dose CT scan.	Canon	04-01-19
US2021012541A1	Apparatus and method using deep learning (DL) to improve analytical tomographic image reconstruction	A method is proposed to improve the image quality of images generated by analytical reconstruction of a computed tomography (CT) image. This improved image quality results from a deep learning (DL) network that is used to filter a sinogram before back projection but after the sinogram has been filtered using a ramp filter or other reconstruction kernel.	Canon	07-11-19
US2021192809A1	Tomographic image reconstruction using artificial intelligence (AI) engines	A method includes obtaining two-dimensional (2D) projection data and processing the 2D projection data using the AI engine. AI engine may involve: generating 2D feature data by processing the 2D projection data using the multiple first processing layers, reconstructing first three-dimensional (3D) feature volume data from the 2D feature data using the back-projection module; and generating second 3D feature volume data by processing the first 3D feature volume data using the multiple second processing layers.	Varian Medical System	12-20-19
EP3367329A1	Denoising medical images by learning sparse image representations with a deep unfolding approach	Method is for machine learning sparse image representations with deep unfolding and deploying the machine learnt network to denoise medical images.	Siemens	02-22-17
WO2019060843A1	Image reconstruction using machine learning regularizers	A method for reconstructing an image of a target object using an iterative reconstruction technique can use a machine learning model as a regularization filter.	Nview Medical Inc	09-22-17
US2021118204A1	Method for reconstructing incomplete data of x-ray absorption contrast computed tomography based on deep learning	A deep learning-based method is proposed using a filtered back projection (FBP) algorithm to obtain an initial reconstructed image; forward projecting the initial reconstructed image to obtain artifact-contaminated complete projection sequences; using a DL technique to process the artifact-contaminated projection sequences to obtain artifact-free projection sequences; using the FBP algorithm to reconstruct the artifact-free projection sequences to obtain a final reconstructed image.	Beihang of University	10-18-19
US2021118200A1	Systems and methods for training machine learning algorithms for inverse problems without fully sampled reference data	A self-supervised training of machine learning (ML) algorithm is proposed for reconstruction in inverse problems. A physics-based ML reconstruction can be trained without requiring fully-sampled training data.	University of Minnesota	10-21-19
US2018018757A1	Transforming projection data in tomography by means of machine learning	A method is proposed for transforming low-quality projection data into higher quality projection data using of a machine learning model.	Suzuki Kenji	07-13-16
WO2018236748A1	Deep learning-assisted image reconstruction for tomographic imaging	An iterative image reconstruction method produces a plurality of intermediate images and to produce the image of the subject. One selected intermediate image from the plurality of intermediate images using a quasi-projection operator. The quasi- projection operator uses a deep-learning model configured to map the at least one selected intermediate image to at least one regularized intermediate image.	University of Washington	06-19-17
EP2890300B1	Supervised machine learning technique for reduction of radiation dose in computed tomography imaging	A technique is proposed for converting low-dose (LD) CT images to higher quality, lower noise images using machine learning.	University Chicago	08-31-12
WO2019074879A1	Image generation using machine learning	A machine learning algorithm is used to generate a final image from an input image generated using a less computationally intensive algorithm.	GE	10-11-17
WO2018187020A1	Tomographic reconstruction based on deep learning	Tomographic transform(s) of measured data obtained from a tomography scanner is used as an input to a neural network. More layers of the neural network are used as wavelet filter banks.	GE	04-05-17
US2019104940A1	Apparatus and method for medical image reconstruction using deep learning for computed tomography (CT) image noise and artifacts reduction	A method is proposed to reduce noise and artifacts in reconstructed medical images using a deep learning (DL) network.	Canon	10-06-17

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Table 2. Representative Patent Literature for Motion Compensation, Metal Artifacts, and Material Decomposition

No	Title	Comments	Owner	Priority Date
US2020273215A1	Monochromatic CT image reconstruction from current-integrating data via machine learning	A neural network is configured to learn a nonlinear mapping function from a training data set to map a CT image, which is reconstructed from a single spectral current-integrating projection data set, to monochromatic projections at a pre-specified energy level, realizing monochromatic CT imaging and overcoming beam hardening.	RPI	09-26-17
US2020196973A1	Apparatus and method for dual-energy computed tomography (CT) image reconstruction using sparse kVp- switching and deep learning	A neural network is trained using input images exhibiting artifacts and target images exhibiting little to no artifacts. Another network is trained to perform image-domain material decomposition of the artifact-mitigated images by being trained using target images in which beam hardening and spatial variations in the X-ray beam are corrected.	Canon	12-21-18
US2019130571A1	Method and system for compensating for motion artifacts by means of machine learning	A method is for compensating for motion artifacts by means of machine learning	Siemens	10-27-17
US2019295294A1	Method for processing parameters of a machine-learning method and reconstruction method	A method is proposed for providing a correction dataset for motion correction of a CT image dataset of an object using processing parameters of a machine-learning method.	Siemens	03-23-18
US2019328341A1	System and method for motion estimation using artificial intelligence in helical computed tomography	A method is proposed for estimating and compensating for motion by reducing motion artifacts produced during image reconstruction from helical computed tomography (CT) scan data.	Canon	11-16-16
US2021056688A1	Using deep learning to reduce metal artifacts	An image correction method is proposed by applying a neural network to the uncorrected x-ray image to generate a metal artifact image wherein the neural network is trained to extract residual image content comprising a metal artifact; and generating a corrected x-ray image by subtracting the metal artifact image from the uncorrected X-ray image.	Philips	01-26-18
WO2020033355A1	Deep-learning-based method for metal reduction in CT images and applications of same	A deep-learning-based method is proposed for metal artifact reduction in CT images.	Vanderbilt University	08-06-18
WO2019063760A1	Deep learning based scatter correction	A neural network is trained on simulated imaging data generated by Monte Carlo simulation including simulation of at least one scattering mechanism to convert CT imaging data to a scatter estimate in projection space or to convert an uncorrected reconstructed CT image to a scatter estimate in image space.	Philips	09-28-17

Table 3. Representative Patents for Radiomics

No	Title	Comments	Owner	Priority Date
WO2018220089A1	Machine learning on raw medical imaging data for clinical decision support	A raw diagnostic machine for a medical diagnosis of raw medical imaging data generated by a medical imaging machine as opposed to a medical diagnosis of a medical image conventionally reconstructed from the raw medical imaging data is proposed.	Philips	05-31-17
US2021192810A1	Tomographic image analysis using artificial intelligence (AI) engines	A method is proposed by obtaining first three-dimensional (3D) feature volume data and processing the first 3D feature volume data using an AI engine that includes multiple first processing layers, an interposing forward-projection module and multiple second processing layers.	Varian Medical System	12-20-19
WO2018232388A1	Systems and methods for integrating tomographic image reconstruction and radiomics using neural networks	Computed tomography (CT) screening, diagnosis, or another image analysis tasks are performed using one or more networks and/or algorithms to either integrate complementary tomographic image reconstructions and radiomics or map tomographic raw data directly to diagnostic findings in the machine learning framework.	RPI	06-16-17
US2020311878A1	Apparatus and method for image reconstruction using feature-aware deep learning	A method is proposed to perform medical imaging in which feature- aware reconstruction is performed using a neural network. The neural network is trained to perform feature-aware reconstruction by using a training dataset in which the target data has a spatially-dependent degree of denoising and artifact reduction based on the features represented in the image.	Canon	04-01-19
WO2020214911A1	Method and system for generating attenuation map from SPECT emission data based upon deep learning	A system is proposed for estimating attenuation coefficients from only single photon emission computed tomography (SPECT) emission data using deep neural networks. The method uses an artificial neural network based upon machine learning system to estimate attenuation maps for SPECT emission data.	Yale University	04-19-19
CN111598895A	Method for measuring lung function indexes based on diagnosis images and machine learning	A method is proposed for measuring lung function indexes based on diagnostic images and machine learning.	Suzhou Fuyuan Medical Tech	04-14-20

5. Discussion and Conclusion

First of all, we underline that although *PatSeer ProX* has provided useful information, we are still on the learning curve. We are not familiar with all of the functions and terminology of the *PatSeer ProX* tool. As a result, we believe that hidden information in the *PatSeer* dataset can be further mined. While we believe that we have obtained valuable data in this study, omissions and biases are unavoidable, due to the imperfect coverage of the database, dynamic nature of the field, and the limitations of our capabilities. We apologize if we have made any misinterpretations.

Despite any problems possibly existing in this preliminary patent landscape analysis, we have learned significantly, greatly facilitated by *PatSeer ProX.* Clearly, research and development in deep tomographic imaging has a strong momentum, engages both imaging companies and academic groups, and promises lasting impact on the further research and development as well as market and healthcare. Since the field of deep tomographic imaging is relatively young, more results and data are yet to be collected and analyzed to reveal the patent dynamics in terms of licensing, revenue, and translated outcomes. Also, it may be very informative to use *PatSeer ProX,* or another similar tool, to identify and track emerging areas of AI-based imaging activities.

In conclusion, we have performed a preliminary landscape analysis on patent literature dedicated to deep tomographic imaging. Using the *PatSeer ProX* tool, we have systematically collected and analyzed relevant bibliometric data, and commented on representative deeptomographic imaging patent literature. Finally, we have discussed several issues and future work on some of interesting topics.

Acknowledgments: The authors are grateful for the standard free trial of the *PatSeer ProX* software provided by Gridlogics Technologies, Pune, India (www.patseer.com). In the trial period, Mr. Prashant Nair, Business Development Manager with *PatSeer* has provided excellent technical support.

Conflict of interest: The authors declare no competing interests.

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