

Normalizing Heterogeneous Medical Imaging Data to Measure the Impact of Radiation Dose

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Abstract The production of medical imaging is a continuing trend in healthcare institutions. Quality assurance for planned radiation exposure situations (e.g. X-ray, computer tomography) requires examination-specific set-ups according to several parameters, such as patient's age and weight, body region and clinical indication. These data are normally stored in several formats and with different nomenclatures, which hinder the continuous and automatic monitoring of these indicators and the comparison between several institutions and equipment. This article proposes a framework that aggregates, normalizes and provides different views over collected indicators. The developed tool can be used to improve the quality of radiologic procedures and also for benchmarking and auditing purposes. Finally, a case study and several experimental results related to radiation exposure and productivity are presented and discussed.

Keywords Medical imaging · PACS · ALARA · DICOM · Monitoring · Quality of service

Introduction

During the past decade, there has been a continuous increment of digital medical imaging equipment in medical institutions that already use repositories to store the data produced. They are important in the diagnosis and review processes of radiologic studies. Moreover, it is possible to track each patient's history over the years. However, it is also important to use those systems to support other operational requirements because quality control, productivity and cost effectiveness control issues have been gaining momentum in several countries [1–4]. Hence, improved workflow in digital imaging laboratories is very important in order to achieve a better quality of patient care. Furthermore, it is essential to assess whether it is possible to reach better quality with the same costs or even reduce them [3] without decreasing quality.

The simultaneous increase of productivity and efficiency is not an easy process, including their measurement and assessment. Some applications already measure productivity in healthcare information systems [2]. However, they are focused on billing and on the number of examinations performed [5]. Assuring quality of service implies considerable manual work to measure the care flow. A few methodologies and protocols can already be used to achieve this result [6]. However, the continuous measurement of quality indicators is still not performed in many institutions due to several difficulties, namely the lack of widespread access to quality and productivity indicators [7].

The analysis of radiation exposure to which the population is subjected in medical imaging studies is important to identify situations that may represent inappropriate patient exposure to ionizing radiation. However, it can also represent an incorrect use of the acquisition devices, which may have

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repercussions in efficiency and productivity. For instance, in the computed tomography (CT) modality, the excessive usage of radiation levels will reduce the durability of some components, such as the X-ray vacuum tube [8]. Thus, the availability of productivity metrics in a system to monitor radiation exposure is an important requirement.

Medical imaging repositories should store all studies performed in institutions. Besides the demanding task of continuously monitoring all imaging studies [9], the produced dose information varies according to the manufacturer or the use of different digital imaging and communications in medicine (DICOM) services (such as DICOM C-STORE with RDSR or DICOM MPPS). They can even use diverse approaches to provide the same information. DICOM standard [10] defines storage and communication processes in medical imaging and also has an information model. However, the semantic and information element terminology are not normalized [2, 4, 11]. There are different metrics measurements and different nomenclatures to represent the same information. Moreover, it is also possible to have data stored in private attributes, which creates major problems when implementing a vendor-neutral solution [12, 13].

The integration and aggregation of this information is not straightforward due to the described lack of standardization. Thus, normalization processes are usually manual, executed by clinical researchers and published in several scientific articles [11, 14–18]. Furthermore, many information elements are not currently accessible but could help clinical staff and also institution managers to tackle the problem. The challenge is to find a way to analyse these metrics in an efficient, effective and convenient manner. For that, normalization of the data provided from different medical devices is a key issue.

In this paper, we propose a methodology to extract, normalize and aggregate information that can be used, for example, in monitoring productivity, and efficiency analysis scope, such as dose radiation measurements. It allows us to normalize and aggregate information from several departments and medical institutions and to map the contents produced by different manufacturers and protocols. The framework also allows us to establish benchmarks and compare the results produced.

Background

DICOM Standard

DICOM standard not only grants basic connectivity between imaging devices but also supplies guidelines for workflow in an imaging department. Nowadays, it is a major contributor to the exchange of structured medical imaging data, and almost all medical imaging manufacturers are following the DICOM rules.

It supports different kinds of information, including distinct modalities of image (CT, XA, US and many others), reports and waveforms. Besides the image, the DICOM file contains the metadata header with information related to the patient, clinical staff, medical institution, acquisition device, exam conditions, clinical protocol and many other relevant pieces of clinical information (Fig. 1).

It is necessary to know the information object definition (IOD) to encode or decode a DICOM object [19]. IOD is very similar to the templates approach, which means that each DICOM object is carried out by specific IODs in a high-level definition. The idea is to represent the most common data types in medical digital imaging. They are a hierarchy, and one single IOD may be a subset of other IODs. For instance, the CT image modality IOD contains the “Patient Information Object Definition” IOD. However, this sub-IOD is also used by other modalities. A SOP instance [19] is an instantiation of an IOD that also contain service specification, which means it has real attributes representing the definition.

Collecting DICOM Metadata

In the medical imaging arena, there are several ways to obtain the metadata information. One possible way is to have access to the DICOM object stored in the PACS archive server. Usually, the metadata stored in the medical imaging objects contains more information than what is typically accessible in traditional PACS databases. For instance, it is not possible to know the number of patients with dose levels above the reference levels.

The images stored in DICOM format have various meta-attributes that could be used to extract metrics associated with department productivity and quality of patient care. Nevertheless, there are several limitations to using this information effectively. The first problem is that collecting the metadata means accessing the DICOM object attributes that are not typically extracted and stored in PACS databases. Hence, we used Dicoogle [20], an open source software PACS able to access every meta-attribute in the DICOM object. Moreover, Dicoogle supplies a RESTful API, which expedites integration with third-party applications. However, accessing all metadata information does not solve the problem by itself. It is also necessary to map and normalize the attributes of images produced by distinct modalities.

Radiation Exposure Analysis

A negative aspect of performing some medical exams is undesired patient exposure to X radiation, which can be recorded in different ways according to modality and manufacturer. For instance, in the computer radiology (CR) modality, the exposure factors associated with each captured image are not stored

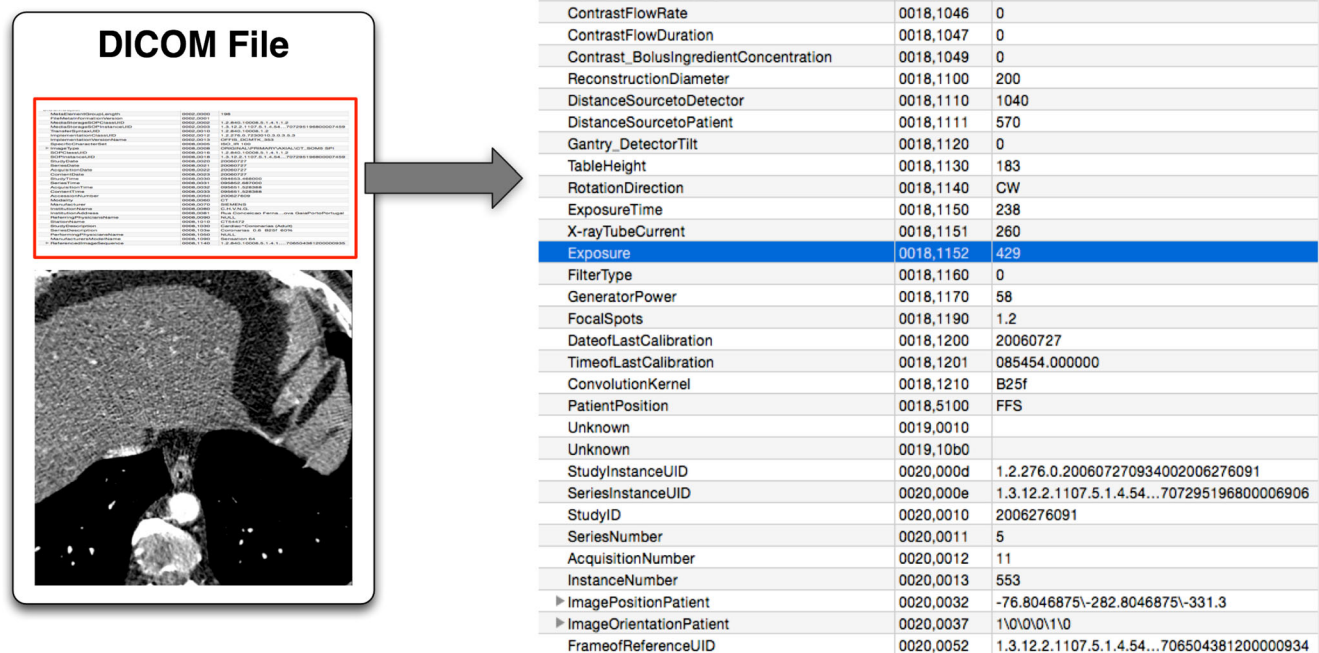


Fig. 1 DICOM metadata from an image file

in the DICOM object metadata. In CR, the attribute that can give us an indication of the radiation level is the exposure index (EI) [21, 22]. Nevertheless, this index does not represent the radiation dose absorbed by the patient, only the information about the suitability of the exposure that the detector has been submitted to, compared with a reference value [23]. For instance, in the CR modality the exposure factors associated to each captured image are not stored in the DICOM object metadata. This is determined as a median of logarithm pixel values in the main histogram lobe or the average value of the pixels that contribute to the image histogram formation, depending on the manufacturer.

Related Work

The quality of DICOM metadata depends on several factors, such as the manufacturer, the configurations of the device, and the information provided by the modality worklist and also from the operators [11, 17]. Nevertheless, the quality of the information is not usually measured because it is not used for the clinical practice. In this section, we will discuss several studies that take advantage of DICOM headers to extract relevant information and knowledge from them [24]. Nevertheless, normalization of DICOM metadata can help, at least in two distinct studies: radiation exposure [25] and productivity of digital imaging laboratories [14].

Besides technical solutions, some related literature focuses on measuring radiation exposure in several modalities, for

instance, in mammography or CT [4, 26, 27]. The CT modality is an intensive device that applies radiation to organs in the patient's body depending on the type of exam. Thus, it is fundamental to have a tool to measure the dose applied to different patients with similar characteristics, such as the body part examined, age or weight. Unfortunately, many countries do not have this kind of control [12]. Several articles propose different methods of measuring the deterministic dose applied in different modalities, with different manufacturers. Nevertheless, these procedures involve manual work by different clinical researchers to store the metadata.

In the literature, some articles already explore the effects of cumulative radiation exposure [28–30]. Moreover, the authors refer to several interesting methods to reduce the cumulative radiation risk in the patient. In order to improve the quality of patient care, the continuous monitoring, analysis and benchmarking of these results should be carefully taken into account, and it is not possible without normalization of how the information is provided [1]. Some studies already describe metrics and propose methodologies to measure the quality of services provided, for instance, the methodology described in [31].

Curtise et al. [31] presented automatic dose data mining for computer radiology (CR) modality. They also provide some statistics, such as mean, standard deviation, low and high quartile and a several others. While other works are focused on dose measurement for one only manufacturer [32], this work extracts indicators from different manufacturers. The system output is a comma-separated values (CSV) file containing only metrics associated with measuring exposure

indicators. The authors present a case study to assess the quality of the protocols applied to patients.

In addition, measuring the department's productivity or monitoring parameters that have a direct influence on patient care is extremely important, especially if they can be related to radiation exposure due to the great amount of exams that patients undergo. The population has an increased need for medical services, which gradually become more complex, and imply the acquisition of new and more expensive imaging equipment. Thus, healthcare institutions that have to make major investment in equipment, are obviously interested in the optimization of workflows and resource usage. Hu et al. [2] show efficient metrics for imaging device productivity. While, in this case, the modality is outside the scope of radiation measurements proposal, the metrics and the methodology to gather the data, and how they build the information system shows that the DICOM metadata are powerful and can be used in different areas. The authors propose five different metrics for monitoring productivity in a magnetic resonance (MR) device. These metrics are: examination duration, table utilization, inter-patient time, appointment interval time and inter-series time. The information is extracted from the DICOM object's metadata stored in the PACS archive. The system is able to parse all DICOM files and extract the relevant information. It is possible to see the reports on a web interface and receive email alerts.

Quality, Research and Public Health (QRPH) is an integrating the healthcare enterprise (IHE) profile [33] and one of the initiatives that intend to extract some data that could be used to measure the quality and efficiency of the institutions. The main objectives are sharing relevant information about quality improvement, strengthening the liaison between the primary care system and clinical research and providing population-based health surveillance. The three different components of the QRPH domain are all dependent on the secondary use of data gathered in clinical care. QRPH allows stakeholders to focus on the workflow cycle of data queries and selection of population studies within the clinical record. It also incorporates the output from the query specification within the clinical system workflow to allow clinical decision support and define profiles for adverse event reporting, anomalies or other important issues.

There are already a few studies, such as [6] intending to normalize the data collected over the medical imaging repositories. Nevertheless, they do not take into account the normalizing problem between different vendors and information systems. Moreover, the authors do not define the benchmark metrics and do not present details about the normalization process and successively apply the normalization process. More recently, Reiner et al. [34] focused on the importance of a standardized method for concurrent optimization of radiation dose and image

quality in medical imaging. The paper points out several directions and creates several theoretical indexes for measuring image quality and creating a safety relation for a patient in a specific exam.

What is principally lacking in previous approaches is the normalization between different manufacturers and DICOM metadata. The proposed solutions did not approach the subject in a broad and interoperable way. Our proposal is mainly focused on creating an integrated way to use different types of information sources that could improve the system. It was designed to provide benchmark indicators that will help to measure the quality from two main perspectives: radiation dose and productivity of the medical devices. The developed system relies on state-of-the-art methodologies that were already developed by other clinical researchers to evaluate the medical workflow and patient dose exposure in a continuous way.

Methods and Materials

Statistical analysis of the medical images repositories and measurement of quality of service is possible, if the information is analysed from a different perspective from the traditional patient-centred one, such as populations, age groups and specific range of periods. Nevertheless, existing workstations do not allow access to data in this paradigm. Access to the DICOM header information is important if this kind of study needs to be performed. In the developed work, we defined a strategy for data gathering from large DICOM repositories. This important process has been achieved with a free and open source tool, named Dicoogle [20]. It is a PACS platform that was previously developed by our group, which provides an important set of functionalities that makes it ideal for supporting the proposed methodology. Information can be extracted from medical imaging repositories when compared to the data provided by workstations' query and retrieval services (DICOM based). Moreover, Dicoogle allows a search of distributed and disperse repositories, and the results can be exported, i.e. DICOM metadata, in CSV format [4]. However, to improve the quality of service, this information needs further processing so that it can be useful for physicians, regulatory services and decision-makers. In order to offer an integrated end-user service, we developed a statistics plugin for the Dicoogle platform [14]. The key feature of this module is the extraction of several metrics from large indexed DICOM repositories. This tool analyses DICOM metadata and allows filtering and classification of specific population characteristics—for instance, looking up breast exams, using the DICOM tag body part examined.

This tool was developed for successful use in healthcare centres, and some results already demonstrated its usefulness [14, 17]. However, the lack of normalized measures hinders its wider adoption, mainly due to dealing with medical devices from different manufacturers or different models of the device. In the sequel, we will propose our developed system to tackle the issue and can work with normalized data across medical devices and institutions.

System Architecture

The ultimate objective of the proposed framework is to support a monitoring system that gathers and aggregates the information of DICOM objects from multiple sources (Fig. 1). For each data source (i.e. PACS archive), a Dicoogle component is used to index the repository DICOM objects (i.e. medical images) and feed the local normalizer with productivity and dose indicators (Fig. 2, institution cache data). The fed information is vendor specific; hence, it is still not ready for integration. The normalizer service receives data gathered in the institution, applies a set of normalization templates and provides the resulting information to the central dose aggregator. Therefore, the normalized information of all participant institutions will be present in the central aggregator. The normalized data

that reaches the central aggregator already follows a uniform format, e.g. grouped by patient age groups and monthly study dates. Due to several privacy issues, patient-specific information is not included at this aggregation level. This strategy provides the necessary raw materials to enable statistical routines over the collected data, supporting different levels of information, i.e. different views of the aggregated data according to the user profile. Moreover, the information may be accessed through a web service interface or exported to CSV or JSON files.

Data Aggregation Services

We developed several services to enable longitudinal studies that can be defined by the user mainly regarding the risks of ionizing radiation inflicted on patients or the productivity of each resource of the dose workflow. Several kinds of studies could be made through our system, e.g.:

- General population view: sample of population defined by gender, age, body region (e.g. chest, head, pelvis) or weight.
- Physician and technician view: distinguishing average dose levels or productivity levels (e.g. number of studies performed per period), oriented to the healthcare professional or group of professionals.

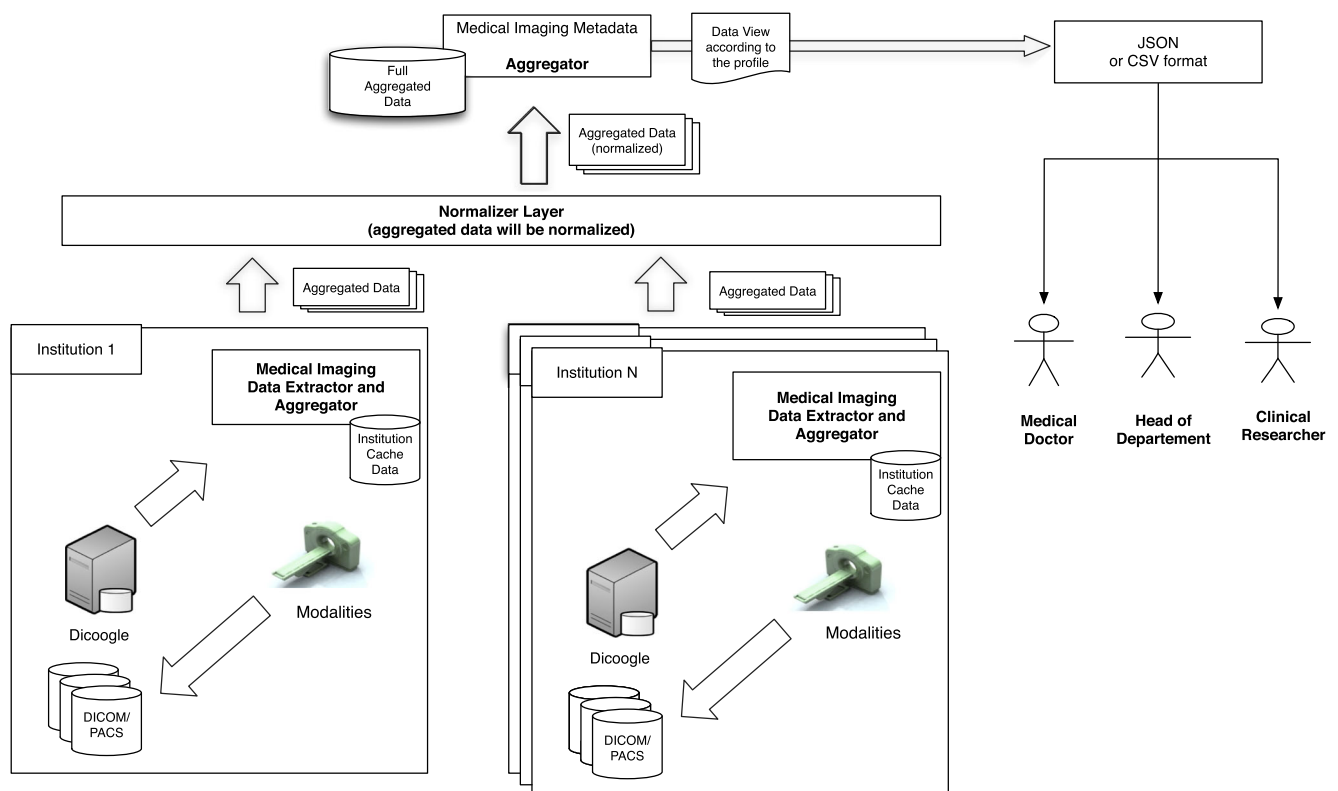


Fig. 2 Normalizing system architecture: data gathering, normalizing and aggregation layer

- Query-based analysis: performing generic queries over the aggregated dose metadata. For instance, finding out the number of patients submitted to high levels of exposure.

Furthermore, medical devices often record the name of the station that acquired the medical images, and so it is possible to group this information and the exam duration by device. With this information, the institution or health authorities may plan resource allocation more efficiently.

Data Normalization Templates

As previously mentioned, the data structure, metric system and even the language used vary according to the manufacturer. In order to achieve flexibility, we created a set of templates to facilitate integration of the system's API. Furthermore, the normalization workflow allows data to be processed in various modules, following a first in, first out (FIFO) strategy (Fig. 3). Through this pipeline, some data analysis operations can easily be performed on existing repositories. Moreover, with this strategy, the pipeline can be parallelized, using MapReduce for instance, if faster data processing is required, namely when dealing with very large archives.

Figure 3 describes the three processes in the pipeline: (1) data gathering, (2) normalization and (3) aggregation. All of the steps are important in order to automatize the process.

Furthermore, it allows the system to be dynamic and extensible to other use cases.

In (1), the medical images are read with Dicoogle and exported to a CSV object, with the image's DICOM metadata, data gathering should be a simple process and does not apply any modification to the data.

The second step, (2), is a normalization process. This is a crucial step to guarantee that the data is measured with the same metrics, thus making the data flow to the other elements of the pipeline in a normalized way. However, as already stated, the normalization is not an easy process. It was split in three distinct modules: filtering, mapping and translation. It is possible to apply several normalization modules over the same input image, for instance, to normalize the dose in a qualitative way or, on the other hand, normalize the dose on a numeric scale. Both can be added to the pipeline as independent normalization tasks. The filter module will define whether to use or discard the input image according to the matchFields defined in the JSON template. For instance, if the template is only for a specific vendor, it will be possible to filter by the manufacturer name (manufacturer tag). Many filters can be added, such as manufacturer, institution name, name of the device and any other DICOM tag. Another module available in the normalization process is the map module, which basically merges two or more fields into one. Different vendors often use different DICOM tags to describe the same information, like, for instance, the body part that was

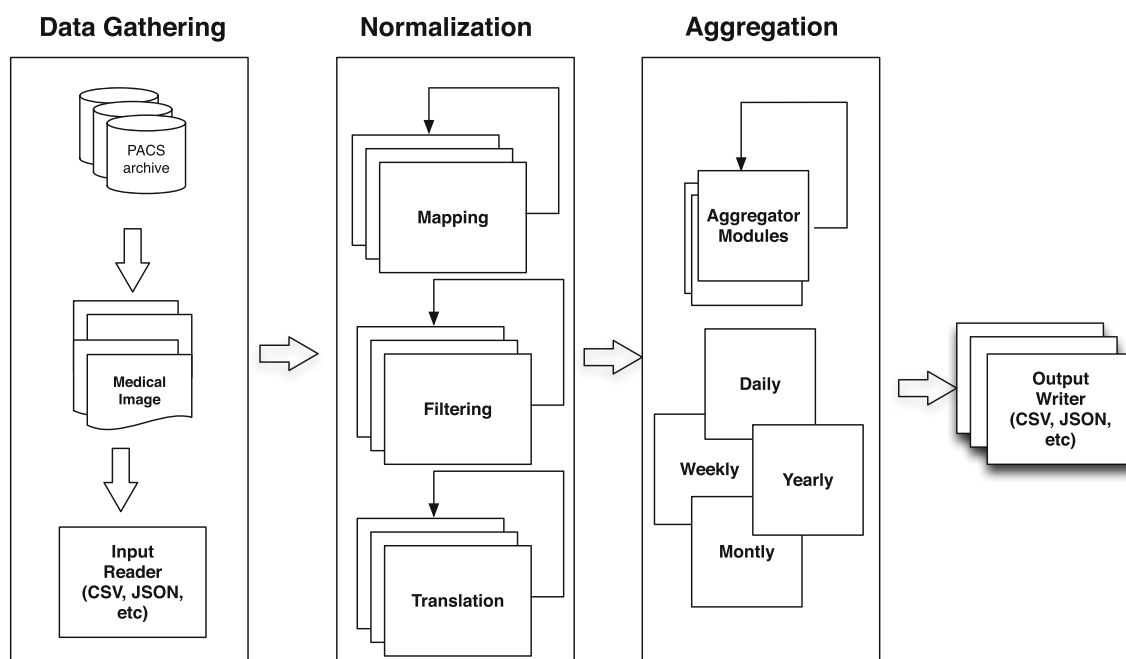


Fig. 3 Pipeline of normalization and aggregation

```

{
  "i18n": {
    "Crânio": "Brain",
    "Joelho": "Knee",
    "Ortopantomografia": "Ortopantomography"
  },
  "map": {
    "AcquisitionBodyPart": "StudyDescription"
  },
  "matchFields": {
    "StationName": [
      "Device1",
      "CTScanner2"
    ]
  }
}

```

Fig. 4 Template mapping original tags into another terminology

examined. Finally, the translation module supports the vocabulary transformation process. For instance, the examined body part could be described with different nomenclatures and different languages according to the configured protocol. Figure 4 shows an example of a harmonization template mapping vendor-specific tags, as well as translations from Portuguese to English.

The aggregation module (3) is used to summarize the information. The supported aggregation functions may rely on the following operations: range, sum, unique, list, min, max, count, percentiles, quartiles, standard deviation and concatenation. The institution cache keeps recording the

information at the image level, and it is transferred already as aggregated data, like, for instance, daily productivity for each modality device or average dose applied daily. It is also important to understand how to work the aggregation processes and how the generated output of the pipeline works. Figure 5 shows an example of the output of the patient distribution in three distinct modalities from an institution.

Finally, Fig. 6 shows part of a more complex template used to support the dose exposure indicators used in our case study. Radiation exposure influences the quality of the acquired image, and therefore, the diagnosis may be affected by the reduction of this parameter [35]. Thus, the proper exposure level should be estimated in order to reduce the risks to the patient and, at the same time, guarantee the image quality. Medical devices often follow an “exposure level index” which is basically the dose level that the modality’s detector has been exposed to [36]. However, as already discussed, these values are recorded on different scales and metrics. Due to the great number of manufacturers and protocols, we also developed extensible modular templates to allow this conversion.

Monitoring System for Radiation Dose

The aggregated view takes into account the user’s profile, i.e. when patient’s information is consulted (in the

Fig. 5 Number of patients by modality

```

{
  "Title": "Number of active patients by Modality",
  "Type": "yearly",
  "Name": "Years",
  "Variable": "Number of active patients by Modality",
  "Filters": [
    {
      "StudyDescription": "Brain"
    },
    {
      "StationName": [
        "Modality_01",
        "Modality_02",
        "Modality_03"
      ]
    }
  ],
  "InstitutionName": "Institution 1"
},
{
  "Values": [
    {
      "Modality_01": "13382",
      "Modality_02": "6081",
      "Modality_03": "465"
    }
  ]
}

```

```

{
  "matchFields": {
    "StationName": "Siemens1",
    "InstitutionName": "Institution 2",
    "StudyDescription": "MAMO",
    "Sensitivity": {
      "Operation": "Range",
      "Values": {
        "0-380": "Low Exposure",
        "380-760": "Normal Exposure",
        "760-1520": "High Exposure"
      }
    }
  }
}

{
  "matchFields": {
    "StationName": "Fugil",
    "InstitutionName": "Institution 1",
    "StudyDescription": "MAMO",
    "Sensitivity": {
      "Operation": "Range",
      "Values": {
        "0-400": "High Exposure",
        "400-800": "Normal Exposure",
        "800-1600": "Low Exposure"
      }
    }
  }
}

```

Fig. 6 Template to normalize exposure indicators from different manufacturers

institution cache data), the monitor retrieves and presents medical exams and doses applied to that particular patient. However, to achieve this functionality, the dosage values provided by manufacturers are not directly understandable and somewhat difficult to merge. Thus, the dose parameters must be normalized to be benchmarked with dose reference levels (DRL) [37] like for instance in computer tomography scope.

On the other hand, radiation experts who understand better the dose exposure risks may adequately estimate the correct dose for each particular patient and clinical case. Since they are familiar with manufacturers' devices and with the recommended dose limits for effective dosage (such as, mSv/year), the information provided through the web services API takes this profile into account. Then again, for a clinician or decision-maker, the information provided is adapted for each profile, e.g. patients' monthly and annual exposure rates, number of exams exceeding the DRL, or productivity indicators, according to equipment or professionals.

Benchmark Metrics

With the dose monitoring system in place, the quality of a service needs also to be measured, using a specific set of metrics [5, 14, 17]. The indicators considered are (a) productivity—exams produced, (b) equipment usage, (c) exam duration, and (d) dose exposure indicators.

Device and Service Productivity

We have defined three quality levels—low, normal and high—their values being defined for each particular equipment and service. After this configuration phase, the monitor system uses these thresholds to produce the reports. This is an important metric to measure the number of patients and exams submitted to each device/service.

Dose/Exposure Metrics

Different manufacturers of medical devices developed distinct measurement exposure scales. Some provide linear scales, as the linear exposure latitude for the imaging plate is very wide, reading sensitivity is needed to be variable (e.g. FujiFilm), and so the exposure indicator is directed inverse with receptor exposure, while others developed logarithmic scales (e.g. Carestream and Agfa) [38, 39]. Several systems—those produced by FujiFilm, Philips and Konica Minolta, for instance—use an exposure index (EI) obtained from the average value of the pixels that contributed to the image histogram, which depends on the anatomy structure that has been acquired [40]. On the other hand, Agfa's equipment uses the logarithm of the median exposure (IgM) which supplies indicators of the suitability of the exposure level the detector has been submitted to, related to a reference level [41].

When analysis of the EI uses equipment from FujiFilm, Philips or Konica Minolta (also known as S value, in this case), the increase in the EI is associated with the decrease of the radiation exposure level the detector has been submitted to. For manufacturers such as Agfa (using IgM index), the increase in the EI value is associated with the increase of radiation exposure level.

Besides metrics normalization, in order to provide a common evaluation scale, we created three qualitative levels from the dose indicators [25]:

- Low exposure: theoretically low quality of the image for diagnosis.
- Normal exposure: the required quality was achieved with the correct radiation.
- High exposure: the patient has been submitted to a high dose exposure level.

Results and Case Studies

The normalization tool was tested with data collected from two Portuguese hospitals. The results presented below are based on the analysis of the generated Dicoogle indexes: the first with 853 MB, resulting from the processing of 121.568

images corresponding to 18.478 patients (522 GB in total); and the second with 20,1 GB, resulting from the processing of 3.008.930 images corresponding to 69.421 patients (1362 GB in total). All data gathering followed an agreement approved by the ethical commissions. Moreover, all data has been analysed in partnership with the medical staff of both hospitals.

Case Study: Dose Normalization

Figure 7 illustrates a useful indicator extracted with our tool: the comparison between doses applied in mammographic projections in two health institutions (CC right, CC left, MLO right, and MLO left)—for each mammography, the acquisition device usually generates four images. Thus, an analysis to see the differences between the applied radiation doses in the two institutions with different manufacturers was made. In this study, 3 years have been evaluated and, thus, it is possible to perceive the homologous year and realize the differences. A normalization process was carried out, assembling 8087 images, from 2047 mammographic studies belonging to 1757 patients collected between 2009 and 2012.

Our methodology allows the comparison between multiple devices, or similar departments, from different institutions. The results are presented in Table 1 that shows, in percentage, the increase or decrease of the number of images acquired with different dose exposures. For instance, on the one hand, it is possible to see that, in proportion, institution B has more exams with high dose in MLO left than institution A, in all the years. On the other hand, the number of high exposure levels

Table 1 Radiation dose levels: comparison between institution B over institution A in mammography incidences. The negative percentage means that the institution B has a lower percentage of images than institution A

Year	Description	Low exposure	Normal exposure	High exposure
2009	CC right	−4%	3%	0%
2010	CC right	0%	1%	−1%
2011	CC right	3%	−3%	0%
2009	CC left	0%	0%	0%
2010	CC left	−1%	−1%	2%
2011	CC left	2%	0%	−1%
2009	MLO right	−2%	0%	2%
2010	MLO right	−1%	2%	−1%
2011	MLO right	0%	3%	−3%
2009	MLO left	−5%	1%	3%
2010	MLO left	1%	−2%	1%
2011	MLO left	−2%	0%	2%

in MLO right has decreased in the last 2 years. We did the analyses with studies that have been acquired for mammography, and it was calculated and used as indicators the first quartile, median and third quartile to study if the detector was hyper-exposed or hypo-exposed.

Case Study: CT Exposure factors analyses

One of the potential interests on study the applied radiation is in the CT modality. The study of the radiation in

Fig. 7 Radiation exposure level in mammography: comparison between number of projections of two institutions



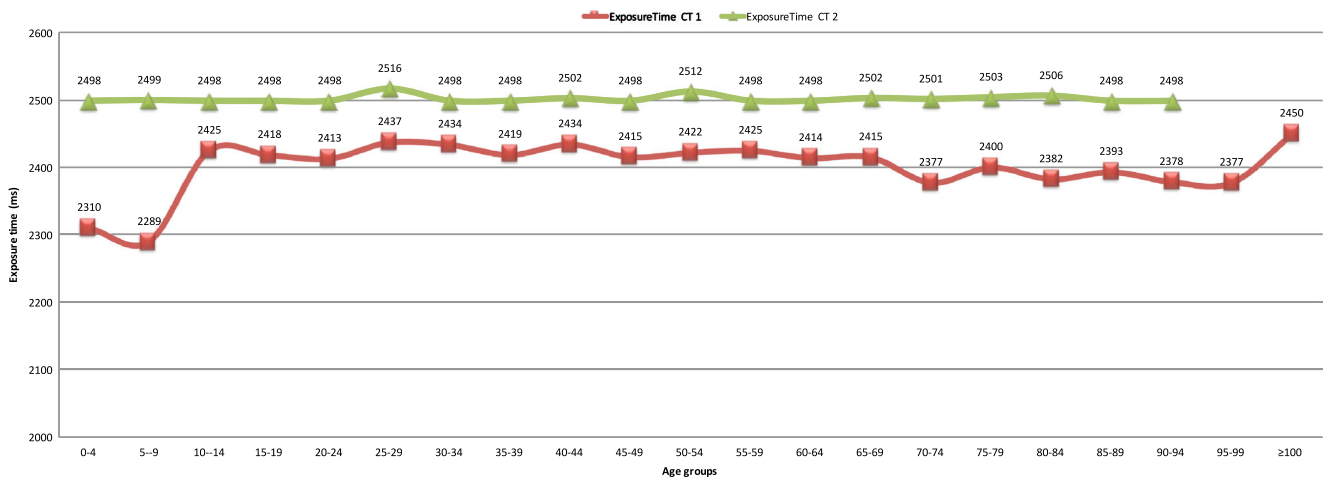


Fig. 8 Variation of the exposure time (ms) in the acquisition of the CT topograms by age groups (average values)

CT is not simple to analyses, and it has several factors that should be evaluated, such as exposure time, KVP, X-Ray current in the tube, CTDIvol and many other factors. For the current study, it was performed and analysed two CT devices from different institutions (CT 1 and CT 2). CT 1 has performed 5339 studies from 4788 patients, and CT 2 has performed 1459 studies corresponding to 1403 patients.

For the current study, exposure time will be analysed using a normalization process to extract and process the data. In this case, the topograms made and their exposure time were analyzed. An important issue while assessing these information is the age groups that are being analysed in 5-year bins (Fig. 8).

While analyses of the exposure time does not require normalization, if we need to identify the variation in the dimension of the topograms, a normalization process will be needed (Fig. 9). The dimension of the topograms is not a value that is appearing in the

DICOM metadata, but it is possible to calculate. For instance, it can be achieved considering the exposure time multiplied by 100 mm to achieve mm/ms or it can also be normalized to cm/s. In Fig. 9, the value has been calculated and analysed. It is possible to see from the analyses that the values of the exposure time and topograms dimensions do not change considerably according to age groups, except in the paediatric population, which was expected. Nevertheless, the main variations are between 0-9 years.

Case Study: Productivity

This normalization case study was extracted from a regional hospital with several institutions in different locations, which makes it more difficult to measure quality. For instance, to audit and track the number of medical devices existing over time and how many studies they are acquiring considering the examination time.

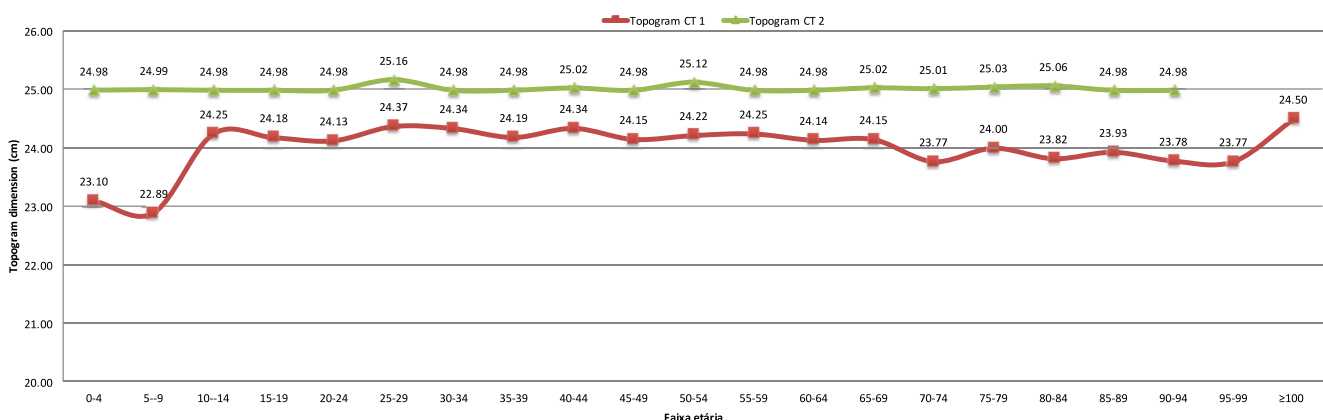


Fig. 9 Variation of the dimension of the topogram (in cm) in the acquisition of CT topograms by age groups (average values)

Auditing these kinds of parameters is not an easy process since most of the hospital information systems or PACS do not record this information in a straightforward way. For example, it was difficult to measure the service productivity considering the number of exams produced per modality. Moreover, if the hospital works 24 h per day/7 days a week, it could be useful to identify the productivity over different time frames. Using the proposed framework, the radiology department director can, for instance, track the radiation dose applied in each device and also the productivity over the years, on a monthly basis. In this case study, the pipeline was configured to extract the productivity indicators of the CT scanners. The normalized study used the following metrics (calculated over the month):

- High productivity: higher than the third quartile
- Normal productivity: between both and the median should be considered normal
- Low productivity: lower than the first quartile

Figure 10 presents one of the productivity charts obtained in this real case study. It is possible to see on which days productivity is below or above the threshold, such as 17 January (left-hand side in the first device) or 3 January (right-hand side in second device). The same can be done monthly or yearly. The normalization process shows that below the first quartile is “low productivity”, and above the third quartile is “high productivity”. “Normal productivity” is in between these thresholds. Finally, the median shows the expected productivity for that device.

Using the reference levels of low, normal and high allows us to make a comparative analysis, taking into account the behavior of the institution (Table 2). Basing the analysis on percentages means interpretation can be independent of the features of the institution's units.

Table 2 Production levels comparison: comparison between institution A and institution B in the production of two different CT devices. Their modulus operandis are different, and the number of produced images is normally different. The table shows a comparison indicator that allows comparison of production levels according to previous performed exams

Devices	Low	Normal	High
Inst. A-CT 1	19%	58%	23%
Inst. B-CT 2	14%	68%	18%

Conclusion

Quality assurance for planned radiation exposure situations (e.g. x-ray, CT) requires the application of examination-specific scans tailored to patient age, body mass index, body region and clinical indication to ensure that the dose for each patient is as low as reasonably achievable for its clinical purpose. We presented a monitoring system that combines heterogeneous dose data from multiple medical imaging archives, measuring their impact according to time frames or groups of people affected by the dose workflow. This is possible due to the system's federative nature: in each participant domain, dose information is collected and sent to a central aggregator that provides a centralized view of the information. This enables audit studies focusing on site productivity and dose statistics of the selected study groups. Furthermore, the radiation indicators are not often measured due to the lack of access to these data and also of normalization processes. With this aggregation software, we provide a baseline system for gathering and normalizing dose metadata present in DICOM objects, which may be easily extended to other use cases and further re-used. Therefore, the presented system provides the means to effectively monitor dose values at several sites, enabling benchmarking and, as a consequence, continuously improving the quality of care provided to patients.

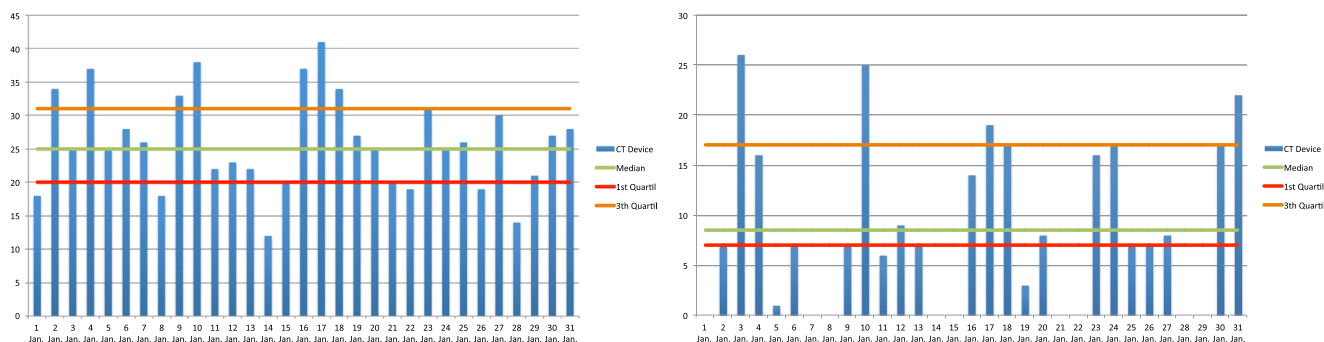


Fig. 10 Productivity of two CT devices: normalization process shows that below the first quartile is low productivity, and above the third quartile is high, normal is in between both

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