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Avaliação Quantitativa das Anormalidades do Parênquima Pulmonar em Imagens de Tomografia Computadorizada do Tórax

Quantitative Assessment of Lung Parenchyma Abnormalities from Chest Computed Tomography

RESUMO

A análise quantitativa de imagens de tomografia computadorizada (QCT) emergiu como uma ferramenta significativa na avaliação de doenças pulmonares, oferecendo vantagens comparáveis aos testes de função pulmonar tradicionais em diagnóstico, estadiamento e prognóstico. Seu benefício único reside na detecção de danos pulmonares antes que as mudanças sejam evidentes em testes de função pulmonar ou mesmo em sintomas clínicos. Além disso, a QCT auxilia na identificação de diferentes fenótipos de doenças, o que é crucial para o tratamento personalizado e a realização de estudos comparativos. Isso é especialmente valioso, pois minimiza a variabilidade subjetiva vista na análise qualitativa. Esta revisão aprofunda-se nos aspectos técnicos da análise de QCT, destacando como essa modalidade de imagem é instrumental no endereçamento de questões clínicas no manejo rotineiro de pacientes com diferentes condições pulmonares. Ela sublinha o papel da QCT em aprimorar o entendimento e tratamento dessas doenças, melhorando assim o cuidado com o paciente.

PALAVRAS-CHAVE

Tomografia Computadorizada de Tórax Quantitativa; Densitometria; Rede Neural Convolucional; Análise de imagem baseada em textura; Rede neural artificial.

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ABSTRACT

Quantitative computed tomography (QCT) has emerged as a significant tool in evaluating lung diseases, offering advantages comparable to traditional pulmonary function testing in diagnosis, staging, and prognosis. Its unique benefit lies in detecting lung damage before changes are evident in pulmonary function tests or even in clinical symptoms. Additionally, QCT aids in identifying different disease phenotypes, which is crucial for personalized treatment and conducting comparative studies. This is especially valuable as it minimizes the subjective variability seen in qualitative analysis. This review delves into the technical aspects of QCT analysis, highlighting how this imaging modality is instrumental in addressing clinical queries in the routine management of patients with several lung conditions. It underscores QCT's role in enhancing the understanding and treatment of these diseases, thereby improving patient care.

KEY WORDS

Quantitative Chest Computed Tomography; Densitometry; Convolutional Neural Network; Texture-based Image Analysis; Artificial Neural Network.

INTRODUÇÃO

Quantitative computed tomography (QCT) imaging offers a non-invasive method to directly visualize, characterize, and quantify lung structures, helping to understand the underlying mechanisms of pulmonary diseases[1–3]. Specifically in lung parenchyma applications, it utilizes various quantitative techniques to assess abnormal and normal lung parenchyma attenuations. These include threshold-based and density-based measures, statistical analysis using histograms, and texture analysis[3]. Additionally, QCT can integrate these features with artificial intelligence for advanced lung parenchyma and airway segmentation[4–6] and classification[7–9], enhancing its diagnostic and analytical capabilities[2,10].

Deep learning models, notably convolutional neural networks (CNNs), have demonstrated superior accuracy in identifying and characterizing thoracic abnormalities that might occasionally escape the human gaze[11–13]. By harnessing these models, radiologists might achieve quicker diagnoses, thus facilitating prompt therapeutic interventions[14–17]. Moreover, the application of AI in chest CT interpretation has shown potential in minimizing inter-reader discrepancies, a long-standing challenge in the field of radiology[18,19].

Emerging studies have underscored the transformative potential of AI in enhancing the sensitivity and specificity of disease detection on chest CT[17]. Furthermore, AI's capabilities extend beyond mere detection. It is now employed in risk stratification thereby streamlining patient management strategies[16,20,21].

Yet, while AI's role in chest CT imaging seems promising, it is crucial to approach its integration with caution[15,22]. Reliability, transparency in algorithmic functioning, and its real-world validation remain paramount. This article delves into the technical aspects of QCT analysis, highlighting how this imaging modality is instrumental in addressing clinical queries in the routine management of patients with several lung conditions.

DENSITOMETRY AS A QCT METRIC OF LUNG DISEASES

Chest CT-scan images are created using multidetector CT (MDCT) technology. In these images, each voxel (a 3D pixel) represents an average linear attenuation value of lung tissue. These values are measured in Hounsfield Units (HU), which range from -1000 HU (pure air) to +3095 HU on 12-bit CT scanners. Specific HU values are given for different substances: -1000 HU for air, 0 HU for pure water, 40 HU for blood, and +1000 HU or higher for cortical bone.

Analyzing the linear attenuation values in lung voxels is key for QCT assessments of lung tissues and other types. Various QCT metrics for obstructive lung diseases are available, such as the percentage of lung tissue with a density less than -950 HU on a total lung capacity (TLC) CT scan, indicating emphysema[23], and the percentage of lung tissue with a density less than -856 HU on a functional residual volume/residual volume (FRC/RV) CT scan, suggesting air trapping and possibly small airway disease[24,25].

At full inspiration MDCT, normal lung attenuation usually ranges from -950 to -700 HU[26], and the proportion of lung falling within this range is referred to as the Normal Lung Index (NLI)[27]. Meanwhile, areas showing higher attenuation between -700 and +50 HU are linked to regions of fibrosis and/or alveolar infiltration[28,29].

In densitometry analysis, density curves representing the percentage of pixels in various lung attenuation categories (low, normal, high) are generated, and basic statistical measures like mean attenuation, skewness, and kurtosis help differentiate the curve shapes between index patients and healthy individuals (Figure 2).

It's important to emphasize that the reliability of these QCT thresholds and metrics is contingent upon the precision and accuracy of measurements taken for each individual or patient. QCT demands greater precision compared to the conventional qualitative lung imaging analysis, as the quantitative values can fluctuate based on lung volumes, CT scan settings, and the calibration of the CT scanner[30].

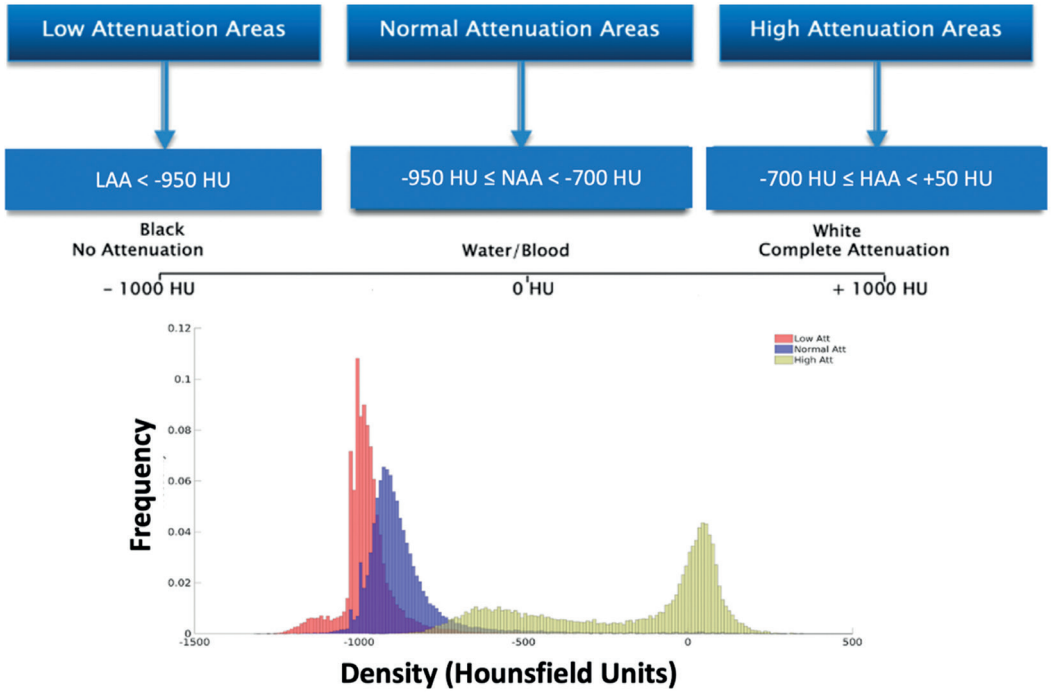

Figura 1. Categories of pulmonary parenchyma voxels based on X-ray attenuation levels using thresholds. These are: 1) Low Attenuation Areas (LAA < 950 HU), 2) Normal Attenuation Areas (- 950≤NAA<-700 HU), and 3) High Attenuation Areas (-700≤HAA<+50 HU). Hounsfield Units (HU) are used as a scale for X-ray attenuation, with -1000 HU indicating no attenuation (air, appearing black on CT) and +1000 HU indicating complete attenuation (bone cortex, appearing white on CT). Density histograms showing pixel percentages in these categories are created after a thoracic radiologist manually identifies each attenuation pattern. These categories often represent low attenuation areas like emphysema (Emph, red), normal lung parenchyma (Well, blue), and high attenuation areas, which are typically ground glass opacities (GGO, yellow), crazy paving and linear opacities (CP/LO, orange), and consolidations (Cons, gray).

A new CT image reconstruction technique, known as iterative reconstruction, has been developed to lower radiation exposure for subjects or patients. This method, introduced by various CT manufacturers, has gained wide acceptance in the qualitative conventional lung imaging field. While there were initial concerns about potential inaccuracies in CT number measurements due to these new techniques, some studies indicate these concerns, despite true, might not be clinically relevant[30,31]. Since, low-dose CT screening for lung cancer is becoming part of clinical practice, it is important to recognize that most mean emphysema indexes increased on the low-dose scans, but the mean difference at all thresholds was less than 3% as previously reported[32].

Finally, another significant limitation of densitometry based QCT is its restricted capability in differentiating lung abnormalities that have similar CT attenuation values. This includes challenges in telling apart emphysema from airspace cystic lesions (Figure 3), as well as differentiating reticulated areas from ground-glass opacities and consolidation. This difficulty arises from the overlapping of attenuation categories, which is evident in the histogram shown in Figure 4.

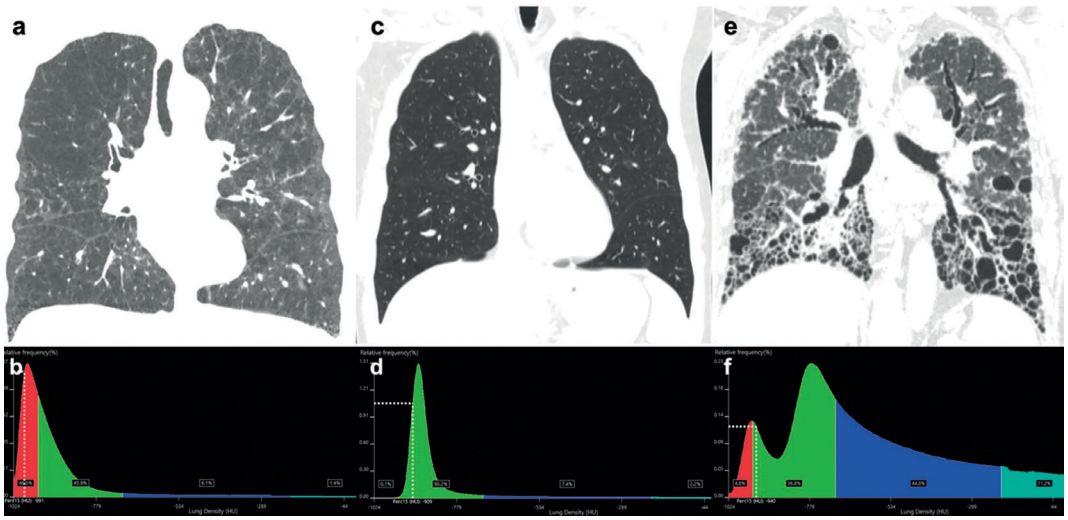

Figura 2. a, b A coronal CT scan with a lung window and lung density histogram for a COPD patient shows a median lung attenuation of –956 HU and an emphysema index (ranging from –1024 to –950 HU, indicated in red) of 46.5%. c, d In a coronal CT scan and lung density histogram of a healthy individual, the median lung attenuation is noted at –882 HU with a normal lung index of 90.2% (spanning –950 HU to –700 HU, depicted in green). This demonstrates a notable peak (kurtosis) and an asymmetrical curve, typically skewed to the right. e, f The coronal CT and lung density histogram evaluation of a severe idiopathic pulmonary fibrosis (IPF) patient reveals a markedly low median lung attenuation of –611 HU, diminished kurtosis (less pronounced peak), a skew towards more symmetric distribution around higher values, and a high-attenuation area percentage (ranging from –700 to +50 HU, shown in blue and light green) of 55,2%.

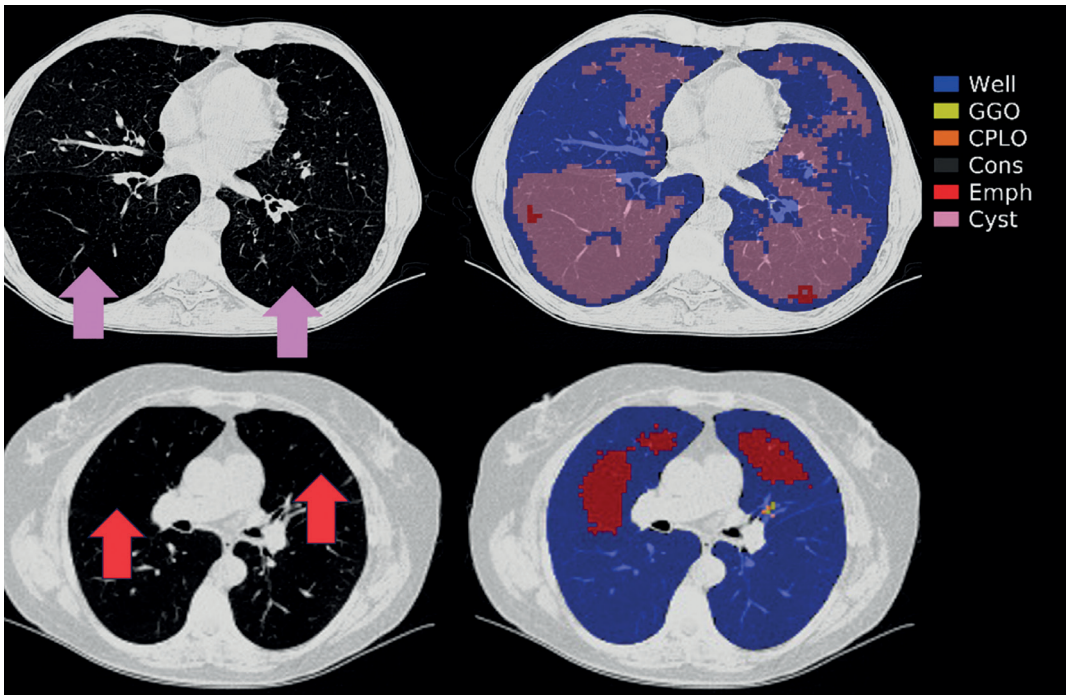

Figura 3. Axial CT scan image obtained in a 54-year-old woman shows multiple low-attenuation areas in a patient with a clinical diagnosis of lymphangioleiomyomatosis (LAM) and in a 53-year-old man with pulmonary clinical diagnosis of emphysema (Emph). Pink arrows indicate air space cysts areas, defined appearing as rounded, low-density (dark) areas due to their air content. The walls of these cysts are thin, and usually predominate in the middle and lower lung thirds. Despite these cysts can vary in size they are typically surrounded by normal. Red arrows indicate a moderate centrilobular emphysema defined as many well-defined centrilobular lucencies, occupying more than 5% of any lung zone. In the right side, each respective image colored with each class identified. (Emph, red), normal lung parenchyma (Well, blue), and high attenuation areas, which are typically ground glass opacities (GGO, yellow), crazy paving and linear opacities (CP/LO, orange), and consolidations (Cons, gray)[33].

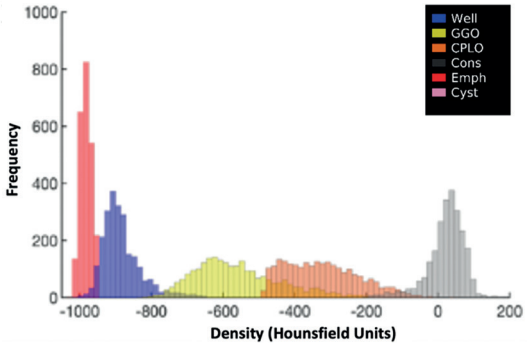

Figura 4. Density histograms showing pixel percentages in these categories are created after a thoracic radiologist manually identifies each attenuation pattern. These categories often represent low attenuation areas like emphysema (Emph, red), normal lung parenchyma (Well, blue), and high attenuation areas, which are typically ground glass opacities (GGO, yellow), crazy paving and linear opacities (CP/LO, orange), and consolidations (Cons, gray). Note the overlapping of each attenuation category.

ARTIFICIAL INTELLIGENCE CONTRIBUTION TO QCT METRIC OF LUNG DISEASES

Artificial intelligence (AI), by leveraging advanced algorithms, especially Convolutional Neural Networks (CNNs), has demonstrated a remarkable prowess in detecting a plethora of chest abnormalities. CNN texture-based analysis employs second-order statistical methods to extract various morphological features derived from imaging. This approach includes techniques like gray-level co-occurrence matrix (GLCM) and run-length matrix (RLM), which consider the spatial interrelations of pixels or voxels within their local contextual framework[34,35].

These textural datasets frequently integrate with machine learning algorithms to facilitate segmentation and classification of CT pulmonary disease patterns. Two prominent algorithms include the Computer-Aided Lung Informatics for Pathology Evaluation and Rating (CALIPER), devised at Mayo Clinic, which quantifies lung parenchyma into five distinct patterns using texture-based analysis, and the data-driven textural analysis (DTA) developed by the National Jewish Hospital group, adept in quantifying the degree of pulmonary fibrosis[3,36]. In recent developments, certain software solutions have acquired registration from ANVISA, positioning them for potential application in clinical practice in Brazil, including core:line (South Korea) and HealthSCAN (Meditec, Brazil).

As a practical illustration, it can be observed that through texture analysis with CNN, differentiation between emphysematous areas and air space cysts is feasible, as well as the assessment of the regional distribution of these lesions (Figure 5).

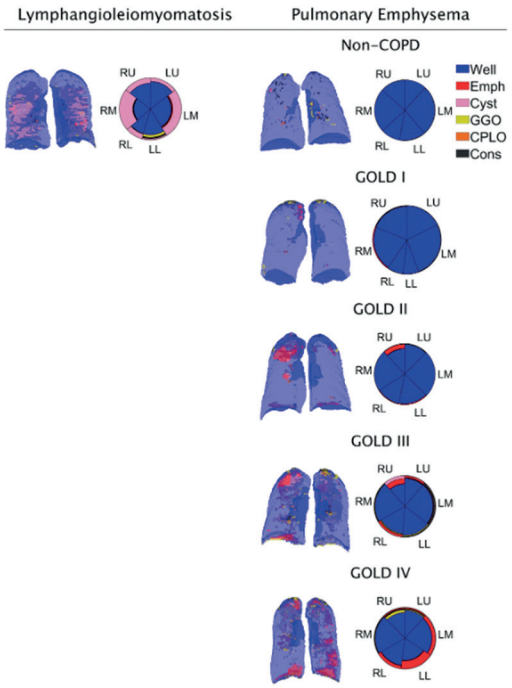

Figura 5. Summary glyphs derived from three-dimensional imaging data (left column) for a representative control case of lymphangioleiomyomatosis (LAM) and cases of pulmonary emphysema with non-chronic obstructive pulmonary disease (Non-COPD) and with mild, moderate, severe and very severe COPD based on GOLD Classification. RU, right upper lung; LU, left upper lung; RM, right middle lung; LM, left middle lung; RL, right lower lung, and LL, left lower lung. Emphysema (Emph, red), airspace cists (Cysts, pink), normal lung parenchyma (Well, blue), Ground-glass opacities (GGO, yellow), crazy-paving/reticular opacities (CP/LO, orange) and consolidation (Cons, gray). Images derived from HealthSCAN software (Meditec, Brazil).

Finally, it is important to highlight that QCT offers a distinct advantage over Pulmonary Function Tests (PFTs) in the context of diffuse lung disease. While PFTs are adept at identifying physiological impairments, QCT excels by furnishing information on morphological alterations in the lung parenchyma, coupled with their spatial arran-

gement. This is particularly beneficial in early-stage disease, where PFT may lack the sensitivity to discern initial aberrations[34]. Consequently, QCT serves as a valuable adjunct to PFT in the assessment of patients with chronic lung disease.

In summary, AI QCT is being used for:

- **Automated Pattern Recognition:** Using CNNs and other deep learning models, AI can be trained to identify the subtle and often complex patterns of ILD and pulmonary emphysema HRCT. This includes recognizing ground-glass opacities, reticulations, honeycombing, and traction bronchiectasis with increased accuracy[37–40].
- **Quantitative Analysis:** Beyond mere identification, AI models can quantify the extent of lung involvement, providing objective metrics like lung volume affected, percentage of fibrosis and/or pulmonary emphysema, and disease progression over time. This quantitative approach aids in monitoring disease progression and response to therapy[16,28,41].
- **Risk Stratification:** By analyzing the patterns and extent of disease, along with clinical data integration, AI can provide risk stratification, offering insights into potential disease progression rates and outcomes[42–44].
- **Differential Diagnosis:** Given the diverse nature of ILD, distinguishing between its various subtypes is often challenging. AI models can aid in this differential diagnosis, recognizing patterns specific to conditions like idiopathic pulmonary fibrosis (IPF), nonspecific interstitial pneumonia (NSIP), or sarcoidosis[45,46].
- **Treatment Response Monitoring**: By providing objective metrics, AI can monitor the response to treatment, allowing clinicians to adjust therapeutic strategies based on quantifiable data, such as reduction in fibrotic regions or improvement in ground-glass opacities[47,48].
- **Integration with Pulmonary Function Tests (PFTs):** AI-driven algorithms can correlate imaging findings with PFTs results, offering a comprehensive view of both the structural and functional aspects of lung compromise in chronic lung diseases[49].
- **Predictive Analytics:** Using vast datasets, AI models can predict potential disease progression, anticipate exacerbations, or even suggest the likely success of various therapeutic interventions based on individual patient profiles[50,51].

In summary, AI is significantly enhancing the capabilities of clinicians in the realm of chronic lung diseases, not only by providing accurate and objective assessments but also by offering predictive insights that can guide management strategies. Recent studies also suggest the growing importance of QCT biomarkers in evaluating acute and chronic pulmonary diseases, providing insights into disease extent, changes in response to treatments, and prognostication for patients.

While these advancements are transformative, the clinical implementation of AI tools mandates rigorous validation, ensuring they maintain high sensitivity and specificity while minimizing false positives. As AI continues to weave its way into radiology, the fusion of machine intelligence and human expertise promises a new era of precision, efficiency, and patient-centric care.

CONCLUSIONS

While these advancements are transformative, the clinical implementation of AI tools mandates rigorous validation, ensuring they maintain high sensitivity and specificity while minimizing false positives. As AI continues to weave its way into radiology, the fusion of machine intelligence and human expertise promises a new era of precision, efficiency, and patient-centric care.

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