COMPUTED TOMOGRAPHY

Single-slice CT measurements allow for accurate assessment of sarcopenia and body composition

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Abstract

Objectives To evaluate the correlation between simple planimetric measurements in axial computed tomography (CT) slices and measurements of patient body composition and anthropometric data performed with bioelectrical impedance analysis (BIA) and metric clinical assessments.

Methods In this prospective cross-sectional study, we analyzed data of a cohort of 62 consecutive, untreated adult patients with advanced malignant melanoma who underwent concurrent BIA assessments at their radiologic baseline staging by CT between July 2016 and October 2017. To assess muscle and adipose tissue mass, we analyzed the areas of the paraspinal muscles as well as the cross-sectional total patient area in a single CT slice at the height of the third lumbar vertebra. These measurements were subsequently correlated with anthropometric (body weight) and body composition parameters derived from BIA (muscle mass, fat mass, fat-free mass, and visceral fat mass). Linear regression models were built to allow for estimation of each parameter based on CT measurements.

Results Linear regression models allowed for accurate prediction of patient body weight (adjusted $R^2 = 0.886$), absolute muscle mass (adjusted $R^2 = 0.866$), fat-free mass (adjusted $R^2 = 0.855$), and total as well as visceral fat mass (adjusted $R^2 = 0.887$ and 0.839, respectively).

Conclusions Our data suggest that patient body composition can accurately and quantitatively be determined by using simple measurements in a single axial CT slice. This could be useful in various medical and scientific settings, where the knowledge of the patient's anthropometric parameters is not immediately or easily available.

Key Points

- Easy to perform measurements on a single CT slice highly correlate with clinically valuable parameters of body composition.
- Body composition data were acquired using bioelectrical impedance analysis to correlate CT measurements with a nonimaging-based method, which is frequently lacking in previous studies.
- The obtained equations facilitate a quick, opportunistic assessment of relevant parameters of body composition.

Keywords Sarcopenia \cdot Intra-abdominal fat \cdot Tomography \cdot X-ray computed \cdot Body composition \cdot Electrical impedance

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Introduction

The individual body composition is an important factor in various clinical scenarios. For example, in emergency care, accurate assessments of body weight would be helpful to correctly calculate dosage of urgent medications and anesthetics [\[1](#page-6-0)–[4\]](#page-6-0). However, determining a patient's body weight in the emergency department may be challenging, as patients might be unresponsive and attending medical professionals often lack the time and technical resources to assess body weight in this setting $[3, 5, 6]$ $[3, 5, 6]$ $[3, 5, 6]$ $[3, 5, 6]$ $[3, 5, 6]$ $[3, 5, 6]$.

On the other hand, obesity has been shown to influence clinical outcomes in patients with diabetes, cancer, and viral infections [\[7](#page-6-0)–[9](#page-6-0)]. More importantly, it has been shown that sarcopenia and sarcopenic obesity are independent risk factors for patient survival and postoperative complications [\[10](#page-6-0)–[15\]](#page-6-0). In contrast to the obvious impact of body composition on human diseases, its assessment is usually not included in routine clinical workup of cancer patients.

Bioelectrical impedance analysis (BIA) represents a widely used method to assess body composition in patients under various clinical conditions including nutritional intervention or fluid management [[16](#page-6-0)–[20\]](#page-6-0). However, the consistency and reproducibility of BIAgenerated data significantly depend on correct measurements and preparation of the patient (fasted state, lack of liquid reservoirs, hormonal cycle in women, etc.). The method therefore demands for prepared integration into clinical routine, but if conducted correctly, BIA data are consistent and highly reproducible [[21](#page-6-0), [22](#page-6-0)]. Other established methods to determine body composition comprise computed tomography (CT), magnetic resonance imaging (MRI), and dual-energy X-ray absorptiometry (DEXA). In contrast to BIA, the usage of CT and DEXA is hampered due to time or adverse effects of radiation exposure [[16\]](#page-6-0).

Given the widespread and frequent usage of computed tomography (CT) in oncological or emergency medicine settings in clinical routine, information about body composition is generated with CT, but not evaluated on a regular basis. Clinically indicated CT scans could therefore serve as a valuable source for anthropometric and metabolic assessments. Previous studies have shown that the determination of total body muscle status is possible by segmentation of skeletal muscles at the height of the third lumbar vertebra [[13,](#page-6-0) [23,](#page-6-0) [24\]](#page-6-0). However, in contrast to the usage of surrogate parameters such as the skeletal muscle index (corresponding to muscle area at the third lumbar vertebra divided by the patient's height squared), correlations between measurements on a single CT slice and non-imaging-based assessment of a patient's total muscle or fat tissue mass are lacking in previous studies. Thus, the purpose of this study was to analyze if clinical anthropometric measures and body composition data derived from BIA measurements, as well as clinical anthropometric data, can be correctly estimated from simple and reliable 2D measurements in routine CT scans and to provide corresponding linear regression models.

Materials and methods

Patient collective

Between July 2016 and October 2017, 62 consecutive melanoma patients admitted to our comprehensive cancer center (Center of Integrated Oncology, University Hospital Cologne, Germany) were included into this prospective analysis. All patients were evaluated per standard protocol with regard to clinical and radiologic staging at initial diagnosis and received additional nutritional status assessment including BIAderived body composition analysis. Written informed consent was obtained from every patient and the study was approved by the institutional review board (No. 16-239, University of Cologne).

Anthropometric and bioelectrical impedance analyses

BIA assessments were performed in overnight-fasted patients within the morning hours using a multi-frequency BIA device (Seca mBCA 515, Seca). Tetrapolar measurements of bioelectrical impedance were performed in an upright position of the patient at 19 frequencies ranging from 1 kHz to 1 MHz [\[25,](#page-6-0) [26\]](#page-6-0). Anthropometric clinical data (body weight, height, and waist circumference) were determined by an integrated scale and standard measures.

CT image acquisition

All CT scans were conducted as required for the patients' oncological management and for routine clinical indications. The acquisitions were performed on three different CT scanners: Philips iCT 256, Philips IQon, and Philips Brilliance 64 (Philips Healthcare), according to the institutions' standard imaging protocols (contrast enhanced, portal venous phase). Eight patients received unenhanced examinations due to renal failure.

All images used in further evaluation for the purpose of this study were reconstructed in axial plane with a slice thickness of 2 mm and an increment of 1 mm using a hybrid-iterative reconstruction algorithm and a soft tissue reconstruction kernel (iDose 4, level 3, Philips Healthcare).

CT measurements

All measurements were performed by one radiologist (reader 1, DZ, 3 years of experience in abdominal radiology) within the standard DICOM viewing software used in our institution (Impax EE R20, XVII SU1, Agfa Healthcare). The third lumbar vertebra was identified in the sagittal plane and measurements were then subsequently carried out on an axial plane located at the center of the third lumbar vertebra. With the help of a freehanded tool, regions of interest (ROI) were drawn to determine the circumference and the area of the following regions at the aforementioned height: psoas muscles, autochthonous spine muscles, and total cross-sectional area of the

Fig. 1 Example of CT measurements on an axial slice using a freehanded tool to determine the area and circumference of the whole body cross-sectional (green), the area of psoas muscles (red), and the area of the autochthonous muscles (yellow). Regions of interest (ROI) are displayed, providing the area (A) in square millimeters (mm²) and the circumference (U) in millimeters (mm)

patient's body (see Fig. 1). The sum of the individual muscle areas was defined as total paraspinal muscle area.

To evaluate intrareader reliability, measurements were repeated in 15 randomly selected CT scans by reader 1 after a period of 6 weeks to avoid recall bias. Interreader variability was assessed using measurements performed by a second radiologist (reader 2, NGH, 4 years of experience in abdominal radiology) in 15 randomly selected CT scans.

Statistics

Statistical analysis was performed using R 3.6.0 with RStudio 1.2.1335 [\[27](#page-6-0)]. Figures were plotted using the ggplot2 package [\[28](#page-6-0)]. Linear regression models for prediction of body weight, muscle mass, total fat mass, visceral fat mass, and fat-free mass were built using the $lm()$ function and a manual exhaustive search. To indicate goodness of fit, adjusted R^2 values are provided. Concordance correlation coefficients were used to measure intra- and interreader reliability. Continuous variables

Table 1 Detailed patient characteristics. Values are presented as mean with standard deviation given in brackets

are reported as mean \pm standard deviation (SD). Statistical significance was defined as $p \leq 0.05$.

Results

Patient characteristics

Of the 62 included patients, 31 were male (median age 73 (30– 85) years) and 31 were female (median age 60 (31–90) years). All CT and BIA scans were performed before treatment initiation. Detailed patient characteristics are shown in Table 1.

Correlation BIA results and CT parameters

By using patient gender (encoded as 0 for female and1 for male), patient body height, and the CT measurements as potential input variables to our models, we were able to fit linear regression models that allowed for the best possible estimation

of patient's total body weight, muscle mass, total fat mass, visceral fat mass, and fat-free body mass (Figs. 2 and [3\)](#page-4-0).

Patient's total body weight was best estimated using only the patients total cross-sectional body area as input variable for the linear regression model (adjusted R^2 0.886, $p < 0.001$):

For the estimation of the patient's muscle mass, the following model yielded the best performance (adjusted R^2 0.866, $p < 0.001$):

$$
Musicle mass \text{ [kg]} = -46.721 \text{ [kg]} + 0.165 \text{ [kg/cm}^2\text{]}
$$

$$
\times total \text{ paraspinal muscle area [cm}^2\text{]}
$$

$$
+ 0.011 \text{ [kg/cm}^2\text{]}
$$

 \times total cross–sectional area cm^2

 $+31.445$ [kg/m]

 \times patient body height [m]

Fig. 2 a Univariate regression analysis of predicted patient weight and patient weight measured with bioelectrical impedance analysis (BIA) in kilogram (kg). b Multivariate regression analysis of predicted muscle mass and muscle mass measured with BIA in kilogram (kg)

Fig. 3 a Multivariate regression analysis of predicted fat mass and fat mass measured with bioelectrical impedance analysis (BIA) in kilogram (kg). b Multivariate regression analysis of predicted fat-free mass and fat-

Optimal linear regression models were found for total fat mass (adjusted R^2 0.887, $p < 0.001$), visceral fat mass (adjusted R^2 0.839, $p < 0.001$), and fat-free mass (adjusted R^2 0.855, $p < 0.001$), respectively:

Fat mass [kg] = -7.367 [kg] + 0.056 [kg/cm²]

\n
$$
\times \text{ total cross-sectional area [cm2] - 11.413}
$$

\n
$$
\times \text{ gender (0 for female and 1 for male)}
$$

$$
Visceral fat mass [kg] = -2.666 [kg] + 0.007 [kg/cm2]
$$

$$
\times total cross-sectional area [cm2] -1.397
$$

$$
\times gender (0 for female and 1 for male)
$$

Fact–free mass [kg] = -74.670 [kg] + 0.249 [kg/cm²]

\n
$$
\times
$$
 total paraspinal muscle area [cm²]

\n
$$
+ 0.020 \text{ [kg/cm2]}
$$
\n
$$
\times
$$
 total cross–sectional area [cm²]

\n
$$
+ 57.880 \text{ [kg/m]}
$$
\n
$$
\times
$$
 patient body height [m]

free mass measured with BIA in kg. c Multivariate regression analysis of predicted visceral fat mass and visceral fat mass measured with BIA in kg

Estimates and their respective 95% confidence intervals can be found in Table 2. All CT measurement showed excellent intra- and interreader reliability (Table [3](#page-5-0)).

Discussion

Various approaches have been described to assess body composition with CT scans: manual or (semi-) automated muscle segmentation, attenuation-based methods, and volumetric methods [[29](#page-6-0), [30\]](#page-6-0). Commonly, muscle segmentation is carried out at the height of the third lumbar vertebra. At this landmark, the cross-sectional muscle area has been suggested to have a linear relation to the patient's overall muscle mass [[13](#page-6-0), [31,](#page-6-0) [32\]](#page-6-0). However, to be included in the daily clinical routine, simple and reliable measurements are needed. In addition, most approaches using CT and MRI to assess body composition are commonly not compared with non-imaging-based methods, such as BIA and DEXA. This prospective study meets these needs and investigated to which extend simple measurements in axial CT slices can accurately predict parameters of body composition obtained from BIA. We found a strong correlation between patient weight and total lumbar cross-sectional area, whereby patient weight could precisely be predicted using a linear regression model. Similarly, the patient's muscle mass and fat mass could be predicted in multivariate linear regression models with simple equations.

Table 2 Estimates for the linear regression models with the respective 95% confidence intervals given in brackets

	Body weight (kg)	Muscle mass (kg)	Fat-free mass (kg)	Total fat mass (kg)	Visceral fat mass (kg)
Intercept	18.351 (12.392-24.310)	$-46.721(-58.269)$ to -35.172)	$-74.670(-95.807)$ to -53.533)	$-7.367(-11.180)$ to -3.553)	-2.666 (-3.485) to -1.847)
Height(m)		31.445 (23.829-39.061)	57.880 (43.846-71.915)		
Cross-sectional body area cm^2)	$0.080(0.072 - 0.088)$	$0.011(0.008 - 0.014)$	$0.020(0.014 - 0.026)$	$0.056(0.050-0.060)$	$0.007(0.006 - 0.008)$
Total paraspinal muscle area $(cm2)$		$0.165(0.101 - 0.229)$	$0.249(0.132 - 0.365)$		
Gender				-11.413 (-13.635 to -9.191)	$-1.397(0.914-1.879)$

Previous studies were able to show significant correlations between single-slice measurements and compartment volumes, such as paraspinal muscle or adipose tissue volumes [\[29,](#page-6-0) [32](#page-6-0)]. Our results are in line with a study from Geraghty et al who determined important anthropometric parameters from a single CT slice [\[33](#page-6-0)]. However, these studies did not correlate their findings to other established methods, such as BIA, as they only compare imagingbased parameters among each other [[29,](#page-6-0) [32,](#page-6-0) [34](#page-6-0)]. To the best of our knowledge, this is the first study to compare single-slice measurements to a non-imaging-based reference standard. A straightforward determination of essential parameters of body composition, such as patient weight and muscle mass, is essential in the field of sarcopenia, which has received growing attention as a potential predictor of adverse outcomes after surgical interventions or overall survival [\[10](#page-6-0), [14,](#page-6-0) [15](#page-6-0), [35\]](#page-6-0). Sarcopenia and sarcopenic obesity show a clear association with poorer overall survival in various malignant diseases [\[36](#page-6-0)–[38\]](#page-7-0). Due to the aging population worldwide, the role of sarcopenia will play an increasingly important role in patient care [\[12](#page-6-0), [15](#page-6-0)]. Besides, a fast and reliable determination of patient weight might be very beneficial in different clinical and scientific settings, such as drug dosing in polytrauma patients or in a retrospective assessment of weight in closed prospective trials. Currently, the skeletal muscle index is frequently used to depict sarcopenia and is computed by the ratio of muscle area to body height cm^2/m^2) [[23](#page-6-0)]. The parameters available through the presented regression models could hold the potential to provide a more accurate, realistic representation of sarcopenia, for example, the ratio of muscle mass to body weight.

As automated segmentation of anatomical structures and pathologies continues to improve and with the recent advent of artificial intelligence, first automated approaches to assess muscle areas in CT have been reported [\[39](#page-7-0)–[41\]](#page-7-0). However, these approaches are not widespread and manual validation is mandatory.

This study has several limitations that need to be considered. First, the estimation of body composition with BIA is potentially susceptible to mistakes, as a standardization of measurements and patient preparation is indispensable. Especially in patients with fluid shifts or regarding the determination of intra-abdominal fat, the accuracy of BIA seems to be limited in comparison with other established methods, such as DEXA or MRI [[42,](#page-7-0) [43](#page-7-0)]. However, it can be argued that small statistical differences between BIA and other methods might not be of clinical relevance [[18\]](#page-6-0). Since we only included patients with malignant melanoma, a selection bias cannot be ruled out. The proposed equations to estimate parameters of body composition require the cross-sectional area and muscle area at a certain height; therefore, this approach is limited to patients who undergo a CT of the abdomen or a wholebody scan. Furthermore, an additional validation, potentially in a larger patient collective, may be necessary. Manual measurements are likely prone to a higher interor intrareader variability in comparison with (semi-)automated measurements. However, we found an excellent intra- and interreader agreement, most probably due to the simplicity of the measurements.

In conclusion, parameters of body composition with high clinical relevance can accurately be determined in clinical examinations by using simple measurements in a single axial CT slice. By routinely providing such measurements, radiology could strengthen its role in delivering personalized medicine through providing clinical target parameters with only little additional effort.

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Compliance with ethical standards

Guarantor The scientific guarantor of this publication is Daniel Pinto dos Santos.

Conflict of interest The authors declare that they have no conflict of interest.

Statistics and biometry No complex statistical methods were necessary for this paper.

Informed consent Written informed consent was obtained from all subjects (patients) in this study.

Ethical approval Institutional Review Board approval was obtained.

Methodology

- prospective
- cross-sectional study
- performed at one institution

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