

**openPR - A computational tool for CT conversion assessment with proton
radiography**

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(Dated: June 8, 2020)

Purpose: One of the main sources of uncertainty in proton therapy is the conversion of the planning CT in (relative) proton stopping powers. Proton radiography provides range error maps but these can be affected by other sources of errors than just the CT conversion (eg. residual misalignment). To better understand and quantify range uncertainty it is desirable to measure the individual contributions and particularly that associated to the CT conversion.

Methods: A workflow is proposed to carry out an assessment of the CT conversion solely on the basis of proton radiographs of real tissues measured with a multi-layer ionization chamber (MLIC). The workflow consists of a series of four stages: CT and proton radiography acquisitions, CT and proton radiography registration in post-processing, sample-specific validation of the semi-empirical model both used in the registration and to estimate the water equivalent path length (WEPL), and WEPL error estimation. The workflow was applied to a pig head as part of the validation of the CT calibration of the proton therapy center PARTICLE at UZ Leuven, Belgium.

Results: The CT conversion-related uncertainty computed based on the usual Paganetti's rule were overestimated by 500% on the pig head in areas where the proton beamlets did not go through cavities. On the contrary, the range uncertainty was very much underestimated where cavities were encountered by the protons. A correlation was found between these errors and HUs between -1000 and -950, suggesting that the underestimation was probably due to the resolution of the CT rather than to an inaccurate conversion. To reduce these errors, the CT calibration curve was adapted by increasing the HU interval corresponding to the air up to -950.

Conclusion: The application of the proposed workflow as part of the validation of the CT conversion to RSPs shed some light on the different contributions to the range uncertainty and on the way they add up. Our results suggest that the use of this workflow on patients or in a generalized study on different types of animal tissues could potentially reduce up to several millimeters the range uncertainties generally taken into account in treatment planning. All the algorithms required to perform the workflow were implemented in the computational tool named openPR which is part of openREGGUI, an open-source image processing platform for adaptive proton therapy.

openPR

50 Keywords: Proton Radiography, Particle Imaging, Range Uncertainty, Multi Layer
51 Ionization Chamber, CT calibration.

I. INTRODUCTION

Range uncertainty in proton therapy is still a topical problem despite more than one decade of research worldwide aimed at developing means of *in vivo* range verification. In 2012, Paganetti established a famous table quantifying the different sources of uncertainty among which the conversion of the planning computed tomography (CT) image to relative proton stopping powers (RSPs) was referenced as one of the most important¹.

Among the potential solutions to the problem of range uncertainty, proton imaging has benefited from an active body of research^{2,3}. Proton CT, in particular, would directly provide the 3D map of RSPs, relegating to the past the inaccurate conversion of the planning CT. Nonetheless, the implementation of proton CT in the clinic is challenged by physical and engineering considerations. For example, the nature of the anatomical sites that can be imaged by proton CT is constrained by the maximum energy available. In practice, only head and neck cases could benefit from this technology. Another approach to reduce range uncertainty is based on recent studies which show that a correction of the planning CT conversion using simple proton radiography could be satisfactory enough in most of the cases⁴⁻⁷. Different proton imaging systems have been developed during the past decade and can be classified into two categories: list-mode and integrated mode⁸. List-mode proton imaging offers the greatest potential in terms of precision since it provides individual measurements for each of the protons crossing the object. Integrated mode proton imaging, on the other hand, integrates the contribution of every protons during the irradiation time of a pencil beam shot. This kind of acquisition is much less complex both in terms of hardware and data throughput which makes it particularly easy to integrate into the clinic^{9,10}. Nonetheless, this comes at the cost of signal degradations resulting from the presence of lateral inhomogeneities along the path of the beam and, to a lesser extent, from multiple Coulomb scattering (MCS). However, deconvolution techniques can be used to increase the spatial resolution and obtain a satisfactory image to assess the range prediction¹¹.

In a recent publication, Meijers *et al.* used a proton radiography technique relying on a multi-layer ionization chamber (MLIC) to validate their site specific HU-RSP conversion, with measurements performed on animal samples¹². Their results showed that the classic margin rule ($1\text{ mm} + 2.4\%$ when using Monte Carlo¹) was too conservative with regard to the errors that they observed. To obtain a range error map for each animal sample that

was imaged, they implemented a workflow originally proposed by Mumot *et al.*¹³. Namely, the CT scans of the animal samples were imported into the treatment planning system (TPS) and the individual integral depth dose profiles (IDDs) corresponding to the beamlets were simulated. The simulated IDDs were then compared to those measured by the MLIC. Range error maps were eventually obtained by computing for each beamlet, the shift that minimized the squared error between the simulated and the measured IDDs.

The range error maps obtained in the Meijers *et al.* workflow provide information directly related to the importance of uncertainties in proton therapy. Nonetheless, the workflow could be improved in two ways. First, it does not allow to isolate the range error coming from the conversion of the CT solely. This is nevertheless all the more important today with the development of robust optimization methods which requires an estimate of each individual contribution to the overall range uncertainty. The differences in range observed by Meijers *et al.* could in fact come from four main sources: CT resolution and artefacts, CT conversion, modeling of the IDDs by the TPS (range mixing and range straggling modeling) and residual setup errors. For example, they observed that increased range errors were well correlated with intersections between materials of clearly different densities. Previous work had already warned about the extreme sensitivity of range error estimation with respect to small residual misalignment and approximations in IDD modeling in the presence of lateral heterogeneities^{9,11}. Secondly, the workflow relies on simulations carried out by the TPS to estimate the range error. This can be useful to take into account in the range uncertainty assessment, the uncertainty coming from the modeling carried out by the TPS. However, to study the uncertainty associated to the conversion of the CT solely, it is desirable to have a range error estimation method which is independent of any TPS.

In order to overcome this dependence of range error maps on TPS dose calculation, Farace *et al.* had proposed a simple analytical model validated by Monte Carlo simulations and real measurements⁹. This was the foundation stone of two subsequent developments which provided a solution to the aforementioned limitations. First, a CT-proton radiography registration algorithm was developed to correct in post-processing the residual alignment errors¹⁴. Secondly, a deconvolution algorithm was developed in order to estimate a WEPL map without resorting to an intermediate stage of CT-based simulations¹¹.

It is of course desirable to integrate these solutions into the workflow proposed by Meijers *et al.* Therefore, we propose an open-source tool, named openPR, to achieve an end-

to-end validation of the calibration curve with limited impacts of residual misalignment and inaccuracies in IDD modelling. However, adding two steps to the workflow to perform the registration and the WEPL estimation with the deconvolution algorithm cannot be done without taking into account that both methods depend on an analytical model which has been validated only on an anthropomorphic phantom. This is actually a source of additional uncertainty. The validity of this model could indeed vary depending on the structures crossed by the protons and on the beam characteristics. To eliminate this source of uncertainty, we propose to add one more step which consists in a Monte Carlo validation specific to the imaged object.

The whole improved workflow was applied in real conditions as part of the validation of the CT calibration of the proton therapy center PARTICLE at UZ Leuven, Belgium.

II. MATERIALS AND METHODS

The workflow detailed in this section aims to assess the error between the WEPL estimated using the proton radiography data and the WEPL predicted on the basis of the CT with the same HU-RSP conversion as the TPS. In the first instance, we describe the types of data needed as input and the techniques used to acquire them. Then, we detail the entire workflow presented in Figure 1.

This workflow was applied as part of the validation of the CT calibration of PARTICLE. The animal sample used for this purpose was a pig head. Its maximum thickness was just small enough to be crossed by the protons with the energy of 200 MeV which was chosen for the radiography. The pig head included tissues leading to HUs covering the whole range of the calibration curve (except for the parts corresponding to lung and metal) as well as complex structures such as cavities.

A. Proton radiography and CT acquisitions

A single energy CT scan of the pig head was acquired at 120 kV with the in-room SOMATOM Definition Edge CT scanner (Siemens, Germany) which is the same model as the planning CT scanner. The reconstruction was performed with a 512×512 matrix, 512×512 mm² field of view, 1 mm slice thickness, Qr36s\3 reconstruction kernel (according

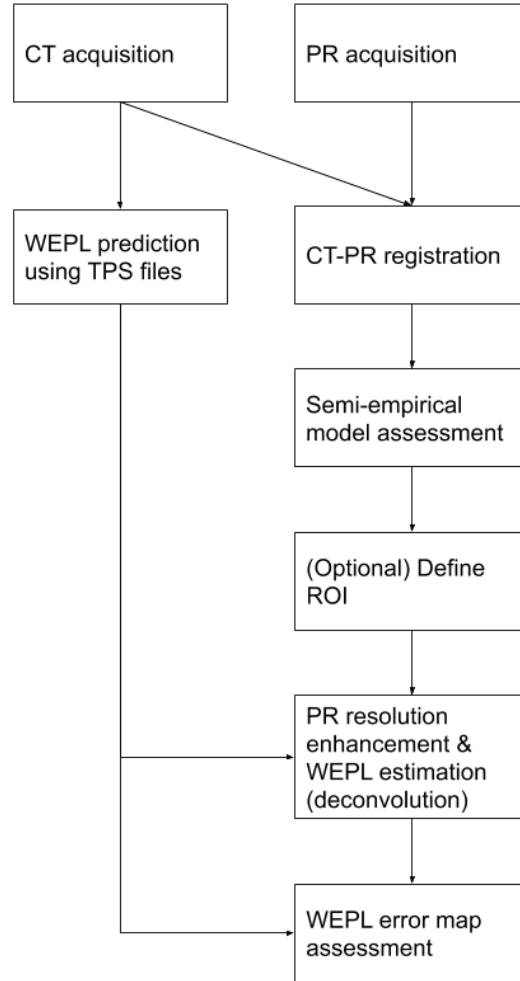


Figure 1: Schematics of the workflow implemented in openPR to assess CT conversion using proton radiography.

to the clinically applicable head scan protocol), iMAR artefact correction for dental filling and beam hardening correction.

The proton radiograph was acquired with the Giraffe MLIC (IBA, Belgium). This device is composed of 180 chambers, each one having a water equivalent thickness of 1.8 mm. It therefore covers the range of protons having an energy up to 230 MeV. However, the nominal energy used in our application was only 200 MeV because the last channels of the Giraffe available at PARTICLE were not calibrated. The MLIC was placed at the proton exit side of the pig head, as shown in Fig. 2. The ProteusOne delivery system (IBA, Belgium) was operated to deliver a map of spots uniformly spaced by 5 mm according to the method established by Farace *et al.*¹⁵ for a ProteusPlus (IBA, Belgium), which we had to slightly

adapt to make it compatible with the ProteusOne. Indeed, with a ProteusPlus, the beamlets are sent according to a scheme known in advance. This makes the proton radiograph easy to obtain by collecting the IDD's measured by the Giraffe for each beamlet sent at a specified location. However, the beam produced by the S2C2 synchro-cyclotron of the ProteusOne system is pulsed, and the dose delivered by each individual pulse cannot be accurately predicted. Therefore, the blind golfer algorithm is used to repeatedly deliver a fraction of the planned dose for each spot, measuring every time the delivered dose and calculating the remaining dose to be delivered. This intrinsic re-scanning delivery would make the analysis of the proton radiography acquisitions more complex. As it is not crucial to know the absolute dose actually delivered in our imaging application, the blind golfer delivery mode was disabled during our proton radiography acquisition.

The pig head was roughly positioned at isocenter using the laser system after the CT scan and before the proton radiography. Accurate alignment was not required since residual misalignment can be corrected in post-processing using a CT-proton radiography registration algorithm¹⁴. A single direction of acquisition was considered with the gantry positioned at 90°, which gave a radiograph along the lateral direction. Since the Giraffe has a restricted field of view (45 x 45 mm²), a whole radiography required several acquisitions between each of which the object was translated. These translations were performed by moving the couch a distance equal to the field of view. The total acquisition time was approximately 10 minutes, which is twice as fast as the time mentioned by Farace *et al.* for a similar radiograph⁹. This reduction in the acquisition time was achieved thanks to the update of the interface provided the manufacturer of the proton delivery system.

B. CT calibration

In the RayStation (RaySearch Laboratories, Sweden) TPS used at PARTICLE, the input needed for CT conversion is a table linking HUs to mass densities. Internally, the TPS interpolates the mass density corresponding to each HU of the CT scan and converts it into one of the materials of its database using a nearest neighbour approach. The stopping power of each voxel is finally computed by using both its estimated mass density and its associated elemental composition.

In order to get the required HU-to-density table, Gammex inserts (Gammex Inc, Mid-



Figure 2: Experimental setup. The MLIC was placed on a lift table and aligned with the laser system.

dleton, USA) were scanned in each one of the three planning CT scanners of PARTICLE, including the in-room one. Average HU values were computed over various protocols and phantoms (a Gammex phantom and two home-made phantoms of a thorax and a head). The differences between measured CT numbers of each scanner were deemed negligible, and only one calibration curve was calculated for all three scanners. To this end, the recommended stoichiometric calibration was used^{16,17}.

C. CT conversion assessment

1. WEPL error map

In the workflow proposed by Meijers *et al.*, the WEPL error is estimated by calculating the shift to be applied to the simulated IDD to minimize the quadratic error between the simulated and the measured IDD¹². This method is, however, not optimal because it does not use the fact that a measured IDD contains information on the WEPL not only at the spot position but also in its vicinity. In a recent publication¹¹, we developed a deconvolution algorithm which takes advantage of this phenomenon called range mixing, to estimate the WEPL map with a higher resolution than that of the proton radiograph. In the present case, the WEPL map was estimated with a resolution equivalent to that of the CT, namely $1 \times 1 \text{ mm}^2$, on the basis of proton radiography data acquired with a 5 mm spot spacing.

In order to establish the error map between the estimated WEPL and that which would

be calculated by the TPS, the two-step conversion method of our TPS, namely RayStation 8.0 (RaySearch, Sweden), was implemented in openPR. To reduce the time spent in manipulations, the alignment between the CT and the proton radiograph was not performed prior to the acquisition using the in-room x-ray alignment system but rather in post-processing with a specific registration algorithm¹⁴. Moreover, we observed that this was more accurate than a conventional kV-kV alignment, as already suggested by the literature¹⁴.

2. *Sample specific validation with Monte Carlo simulations*

Although the tools mentioned above have been evaluated in their respective publications^{9,11,14}, they have limitations related to the imaged object. All these methods are based on a model according to which the proton beamlets propagate in straight lines, parallel to each other, with negligible scattering. These methods assume that a measured IDD, named IDD_m consists of a convolution of a Gaussian kernel G having a standard deviation equal to the spot size with shifted versions of a pristine Bragg curve called IDD_{ref} which corresponds to the IDD that would be measured without the phantom through the beam path:

$$IDD_m(x, y, z) \approx G(x, y) * IDD_{ref}(z + WEPL(x, y)) \quad (1)$$

where z refers to the depth axis of the IDD and (x, y) are the spatial coordinates in the plane perpendicular to the beam.

In this paper, IDD_{ref} was obtained by measuring an IDD under the same condition as for a proton radiography but without any phantom. Therefore, Eq. 1 is referred to as a semi-empirical model throughout this paper.

This approximation was proved to be good enough on several phantoms, including an anthropomorphic head phantom. However, it cannot be excluded that it may fail for some anatomical structures. In particular, the pig head imaged at PARTICLE exceeds both in terms of structural complexity and thickness the phantoms considered in the past.

In order to carry out an accurate analysis of the range error, it is necessary to validate that the analytical model expressed in Eq. 1 and used by the deconvolution and the registration algorithms is correct. To do this, we propose to systematically perform an object-specific validation of the analytical model by Monte Carlo simulations. Indeed, these are nowadays often considered as the gold standard in terms of simulations accuracy, especially in complex

geometries such as the presently used pig head. We thus achieved a validation of our semi-empirical method independently of the TPS with a fast Monte Carlo simulation tool named MCsquare¹⁸ which is part of the openREGGUI platform on which openPR is based.

First, MCsquare was commissioned for PARTICLE. The obtained beam model was evaluated using the in-water validation measurements previously obtained during the validation of the TPS beam data library. Then, the HU-to-SP(R) conversion of the TPS was adapted so as to get the same SP in MCsquare, which uses a different material assignment scheme.

To assess the accuracy of the analytical model, the MLIC was modeled by a water box added in the CT image, at the exit side of the patient. In order to mimic an acquisition with the Giraffe and in particular to take into account its limited field of view, a treatment plan with a specific isocenter was automatically created by openPR for each position at which the object was placed. Finally, the dose maps were exported separately for each beamlet so that the IDD_s could later be reconstructed.

Since the aim of Monte Carlo simulations is to evaluate the accuracy of the analytical model and the deconvolution method also depends on this model, it cannot be used to estimate the WEPL in such context. Instead, the range error, named RE , was estimated by computing the displacement that minimizes the quadratic error between two dose deposition profiles:

$$RE = \left| \arg \min_s \sum_z (IDD_1(z + s) - IDD_2(z))^2 \right| \quad (2)$$

3. Range uncertainty analysis

In his seminal paper on range uncertainties in proton therapy, Paganetti evaluated the range uncertainty to 1.2 mm + 2.4% with Monte Carlo dose calculation and to 1.2 mm + 4.6% with less accurate dose calculation algorithms, such as the Pencil Beam Superposition method¹. The various contributions to the range uncertainty listed by Paganetti are now broadly accepted as a guide for beam-specific PTV margins, or to set error parameters in robust optimization. Therefore, it is highly relevant to set up a methodology to validate those uncertainties using proton radiography. However, this cannot be done simply by comparing the percentage of errors lower than the margin proposed by Paganetti.

First, we note that Paganetti expressed his estimate of the proton range uncertainty as

a 1.5 standard deviation interval. This means that the amount of range errors confined in this interval in fact depend on the probabilistic distribution of the error. For a normal distribution, this approximately corresponds to a 87% confidence interval.

A second element to consider to assess the margin defined by Paganetti is that it takes into account patient setup errors and uncertainties in the modelling of range degradation. However, those should be considered as negligible in the present study thanks to the accurate registration in post-processing and to the validation of the semi-empirical model against Monte Carlo. Estimating the remaining range uncertainty the same way as Paganetti did, we obtain a 87% interval given by $0.6 \text{ mm} + 2.4\%$. From there, we can assess the relevance of the margins used so far by comparing the percentage of range errors lower than $0.6 \text{ mm} + 2.4\%$ to the expected value, namely 87%.

D. openPR

All the algorithms involved in the workflow described above were implemented in openPR which was developed as a plugin in openREGGUI, an image processing open-source platform for adaptive proton therapy. The code is mainly written in Matlab (MathWorks, USA) and is available on the openREGGUI main repository (openreggui.org). The user can interact with the data and call the methods either via a graphical interface or through the scripting functionality available in openREGGUI. The features offered by the graphical interface also cover data import, data and metrics visualization, region of interest drawing, etc. In addition, several options were made available for the various methods. For example, a registration can be performed either with one proton radiograph or with two orthogonal proton radiographs. Parameters such as the spot spacing and the number of spots can also be adapted by the user.

III. RESULTS

A. Sample specific validation with Monte Carlo simulations

By applying CT-proton radiography registration in post-processing, we could reduce the impact of set-up errors and therefore remove them from the several possible contributions to the range error. Consequently, the remaining major sources of errors were, in accordance

with the table established by Paganetti¹, an inaccurate conversion of HUs to RSPs, an insufficient resolution of the image acquired by the CT or CT artefacts. This assumes that the semi-empirical model used by most of the algorithms implemented in openPR was accurate. Although this model was validated both experimentally and using Monte Carlo simulations in a previous publication⁹, the absence of a scattering model could be prejudicial in the current case where many cavities and heterogeneous structures are present. This example demonstrates the need for the systematic validation step based on Monte Carlo simulations that we added to the workflow.

The range error depicted in Fig. 3 shows overall an excellent agreement between Monte Carlo and semi-empirical simulations except in the upper left corner. Some Bragg curves selected at arbitrary locations are also shown. They correspond to the centers of areas A, B, and C of Fig. 4, which will be discussed in the next section. An IDD representative of the area where the error is greater was also selected at the location named E. An explanation for these errors is that the semi-empirical method is based on a constant spot size, typically defined at isocenter, and does not account for scattering properties. Bone tissues, or air gaps between tissues, for example, can thus lead to important discrepancies between Monte Carlo and semi-empirical simulations.

The map of range differences between semi-empirical simulations and Monte Carlo simulations was used to draw a region of interest in which 90% of the error is below 0.5 mm, as shown on Fig. 3.

B. Range uncertainty analysis

Fig. 4 shows the absolute difference between the WEPL predicted using the calibration curve of our TPS and the WEPL obtained via a sparse deconvolution of the proton radiography data, after registration with the CT. The error appears to greatly vary depending on the location. The biggest discrepancies are in the ears. However, they are outside the region of interest drawn in the previous section. In addition, these organs may have moved between CT and proton radiography acquisitions, which is why we will not analyze them. Other important errors take place in cavities, and in a particularly remarkable way in the sinus cavities.

Several areas have been drawn on Fig. 4. They correspond to distinct levels of errors but

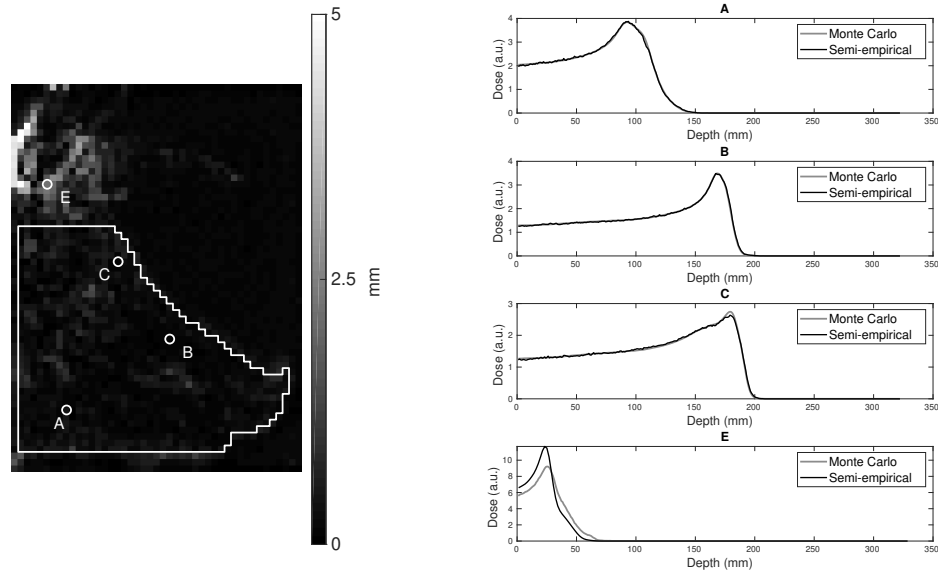


Figure 3: Range difference between semi-empirical simulations and Monte Carlo simulations. 90% of the values inside the region of interest are lower than 0.5 mm.

also to different underlying tissues. Area A has the lowest error and does not contain any
cavity. Area C, on the other hand, presents the highest error and corresponds to the sinus
cavities. Area B has moderate errors and its underlying tissues are made out of cavities,
bones and soft tissues. Area D is the region of interest determined following the sample
specific validation of the analytical model by Monte Carlo simulations.

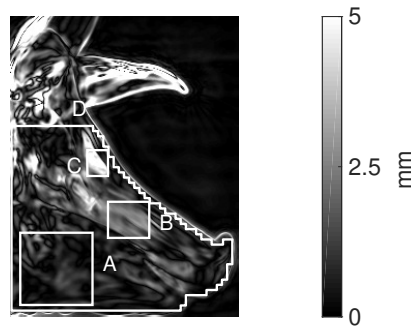


Figure 4: Absolute error between the WEPL predicted using the calibration curve of our TPS and the WEPL obtained via a sparse deconvolution of the proton radiography data.

Table I lists in its first column, the percentage of WEPL errors (PWE) which are lower

314 than the range uncertainty of $0.6 \text{ mm} + 2.4\%$ calculated according to Paganetti's definition.
 315 Except for area C, the margin was clearly overestimated with more than 91.1% of the errors
 316 lower than the margin. Region C which corresponds to the sinus cavities constitutes a
 317 very problematic particular case. The validation previously carried out with Monte Carlo
 318 simulations makes it possible to rule out any modeling error. We believe that the cause of
 319 this discrepancy is to be sought at the level of the anatomical structures present within these
 320 cavities. These have many transitions between thin cartilages and hollow regions where CT
 321 resolution may be problematic. In particular, these cavities present HUs with values lying
 322 between -1000 and -950. These are intermediate values between air and pulmonary tissues.
 323 Consequently, it was decided to extend the range of HUs corresponding to air, ie. having
 324 an RSP of 0, up to $\text{HU} = -950$. The second column of Table I lists the results obtained
 325 with this correction. It did not only have a positive impact in the areas with cavities where
 326 10.6% of additional pixels were found in the margin but also in all the other regions with a
 327 general improvement of a few percents.

Area	PWE before correction	PWE after correction
A	99.8%	100.0%
B	91.1%	99.3%
C	35.9%	46.5%
D	95.4%	97.9%

Table I: Percentage of WEPL errors (PWE) confined in a $0.6 \text{ mm} + 2.4\%$ margin in areas
 A, B, C, and D of Fig. 4 before and after that the calibration curve is adapted.

328 In their paper, Meijers *et al.* calculated the ratios of the range error and the uncertainty
 329 margin. They found out that 1.5 standard deviation of the values did not exceed 75%. This
 330 actually means that the margin was overestimated by at least 25% for approximately 87%
 331 of the spots (assuming a normal distribution which seems valid with regard to their figure.).
 332 For the sake of comparison with Meijers' results, we did a similar experiment. However, we
 333 considered a 90% confidence interval rather than a 1.5 standard deviation interval, because
 334 the number of errors contained in the 1.5 standard deviation interval depends on the shape
 335 of the error distribution. It would be 87% for a normal distribution but it is different for
 336 non perfectly Gaussian distribution. The percentage of WEPL errors lower than the margin

is plotted on Fig. 5 for various margin sizes ranging from 0.6 mm + 0% to 0.6 mm + 5%. In the region of interest D which includes area A, B and C, this value is 90% for a margin of 0.6 mm + 1.4% which means that the part of the initial margin of 0.6 mm + 2.4% which depends on dose computation was actually overestimated by 71% for 90% of the pixels, or equivalently could be decreased by 42%, which is similar to Meijers conclusions¹². In the region A which does not have any cavity, the margin corresponding to a 90% confidence interval is 0.6 mm + 0.4%. This means that the part of the initial margin of 0.6 mm + 2.4% which depends on dose computation was overestimated by 500% for 90% of the pixels, or equivalently could be decreased by 83%.

Finally, Fig. 5 b shows the pixels which are confined in a margin of 0.6 mm + 2.4% on the one hand and 0.6 mm + 1.4% on the other hand.

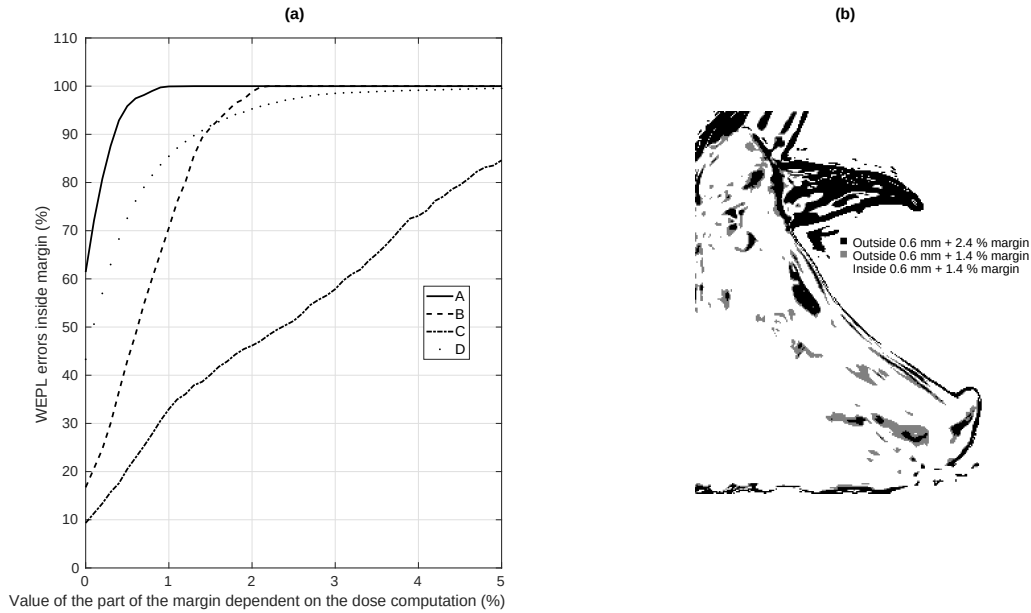


Figure 5: (a) Relationship between the part of the margin dependent on the dose computation and the percentage of WEPL errors confined in this margin, for a pig head. (b) WEPL errors confined in the initial margin of 0.6 mm + 2.4% on the one hand and in the margin of 0.6 mm + 1.4% corresponding to a 90% confidence interval, on the other hand.

IV. DISCUSSION

The use of treatment margins, or more recently robust optimization methods, is necessary to ensure the robustness of proton therapy plans against treatment errors. A major source of uncertainty is the conversion of CT images to RSPs¹⁹. Proton computed tomography would make it possible to obtain a map of RSPs directly and is naturally the ideal modality, but its clinical use in the short term remains an unresolved challenge. On the other hand, proton radiography was recently used to validate the conversion scheme of the proton therapy facility of University Medical Center Groningen (Groningen, The Netherlands)¹². The workflow proposed by the authors made it possible to reduce the range uncertainty, not only by quantifying the error made by the TPS on the RSP computation but also by allowing the HU-RSP conversion to be accordingly adapted.

The workflow detailed in the paper of Meijers *et al.* is based on the comparison of measurements acquired with an MLIC with simulations generated by the TPS on the basis of a CT of the imaged object¹². The output is a range error map intended to assess the CT conversion. Nonetheless, the range difference can come from several sources: CT resolution and artefacts, CT conversion, modeling of the IDD by the TPS (range mixing and range straggling modeling) and residual setup errors. To assess solely the conversion of the CT, it was therefore desirable to adapt this workflow to make it on the one hand independent of the TPS dose computation, and on the other hand robust to residual setup errors. In the present paper, we proposed to include a previously published CT-proton radiography registration method for correcting residual misalignment and a deconvolution method for estimating a high resolution WEPL map from the low spatial resolution proton radiography data, without relying on a TPS. In addition, we showed the importance of adding to the workflow a stage of Monte Carlo simulations in order to validate the use of the tools relying on a semi-empirical model. We have shown that certain particular anatomical configurations such as the ears of the pig head studied throughout this paper, could cause a significant divergence of the beam which is not modeled by analytical simulations. It was thus necessary to draw a region of interest based on this validation.

Our workflow was applied to a pig head in the context of the validation of the CT conversion scheme at PARTICLE. Following Paganetti's table, the range uncertainty was estimated to be 0.6 mm + 2.4%. Large variations in the WEPL were observed to be

related to the presence of cavities. Where no cavity was traversed, the range error was way below the expected value. In contrast, only 35.9% of the range errors were within the margin at the exit of the sinus cavities, using the initial calibration curve obtained using the stoichiometric method. The agreement between Monte Carlo simulations and those relying on the semi-empirical used by openPR confirmed that these discrepancies were not related to the modeling of the dose deposition. The values of the HUs responsible for the errors were between -1000 and -950. These do not correspond to biological tissues but rather to average values between these and the surrounding air. It therefore seems that the error was not really a consequence of an inaccurate conversion but rather of a CT resolution issue or of CT artefacts. We therefore proposed a correction procedure consisting in forcing to 0 the RSP of all HUs between -1000 and -950. No other correlation between the error and specific tissues was found.

After correction of the calibration curve, we obtained values in line with the results presented by Meijers *et al.* regarding the overestimation of the margins, except for the sinus cavities. The overestimation of the margin was 71% for 90% of the region of interest. A margin of 0.6 mm + 1.4% would actually have been enough to guarantee 90% of the WEPL to be confined in the margin. Moreover, the use of proton radiography showed that the range uncertainty can vary considerably from one area to another. For the pig head considered in this study, the classical rules were underestimated in the cavities while they were overestimated by 500% everywhere else.

These observations shed some light on the distinct contributions to the range uncertainty and on how they add up. They seem to confirm that the validation of CT conversions on real biological tissues could potentially improve up to several millimeters the way that the uncertainties are accounted for in treatment planning. A specific use per patient should be possible thanks to the low dose associated with the proton radiography⁹. In addition, a generalized study on different types of animal tissues and across proton therapy centers would make it possible to determine and better understand the existence of correlations between range errors and underlying tissues. All the tools necessary to carry out the workflow presented in this paper are available on the openREGGUI platform under an open-source license. In addition, the use cases of openPR can be extended to any specific need of the user thanks to the scripting tool offered by openREGGUI.

V. CONCLUSIONS

In this paper we developed a workflow to achieve an end-to-end validation of the CT conversion to RSPs in proton therapy using range probe measurements. The proposed method has two advantages over those already published: it mitigates residual misalignment in post-processing as well as potential modeling errors in the dose deposition profiles. The workflow was applied to a pig head as part of the validation of the CT calibration of the proton therapy center PARTICLE at UZ Leuven, Belgium. The results showed that the CT conversion-related uncertainty computed based on the usual Paganetti's rule were overestimated by 500% except where cavities were present. This shows that the validation of CT conversion in a generalized study on different types of animal tissues could potentially reduce by several millimeters the range uncertainties generally accounted for in treatment planning. All the tools necessary to carry out the proposed workflow were made available open-source.

VI. ACKNOWLEDGMENTS

The authors thank the IBA site engineers at PARTICLE for their technical support.

Sylvain Deffet was supported in the confines of this study by the *Fonds européen de développement régional (FEDER)* and the Walloon region in the framework of the operational program *Wallonie-2020.EU*.

Marie Cohilis is supported by the Télévie Grant from the Belgian *Fonds National pour la Recherche Scientifique* F.R.S-FNRS (Grant No. 7450517F).

Kevin Souris is funded by the Walloon region (MECATECH/BIOWIN, grant number 8090).

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