APPLICATION OF AN ARTIFICIAL INTELLIGENCE SEGMENTATION FOR DEEP HYPERTHERMIA TREATMENT PLANNING IN THE PELVIC REGION

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ABSTRACT. During a microwave hyperthermia oncology treatment, the target region temperature is elevated to the temperatures of 40–44°C, which improves the therapeutic effect of a standard radiotherapy and/or chemotherapy treatments. Amplitudes and phases of antenna input signals in the phased array setup surrounding the 3D patient model are optimised with respect to maximise the energy deposition in the target region. In this study, we successfully integrated an automatic artificial intelligence segmentation routine, used for patient-specific 3D model generation, into the hyperthermia treatment planning process. This allows us to apply more realistic patient 3D model for the online hyperthermia guidance including detailed retrospective analyses of the overall treatment quality, possibly leading to a widespread clinical use of the hyperthermia treatment planning.

KEYWORDS: Hyperthermia, specific absorption rate, phased array applicator, hyperthermia treatment planning.

1. INTRODUCTION

Microwave regional hyperthermia is an oncology treatment during which a target region is heated to the temperature range of 40–44°C for the duration of 60–90 minutes [2]. It is typically applied in combination with radiotherapy or chemotherapy, utilising constructive interference from multiple external electromagnetic field (EM) sources, converted into a heat within the human body [2,3]. Individual EM waves are produced by the antennas surrounding the body and forming the phased array regional hyperthermia microwave system [2,3]. Amplitudes and phases of individual antenna input signals are optimised in order to obtain maximum energy deposition within the target region [3,7]. This is achieved by applying the hyperthermia treatment planning (HTP) process in which a patient-specific 3D models created from computed tomography (CT) scan in combination with a model of the microwave phased array system for EM field simulations and optimisation is used [3,7].

HTP is applied for online clinical guidance, the amplitudes and phases of individual antennas input signals to be adjusted during the treatment, if high temperature is measured outside the target region or if the patient complains [10,11]. It is also used as an inclusion criterion for the hyperthermia treatment (HT) to test whether it is possible to heat selected target or if it is safe for the patient to undergo the treatment [12]. HTP also allows a detailed retrospective analysis of the entire treatment process and design of novel applicator systems [13,14]. For all HTP applications, the patient 3D model is pivotal for a correct implementation of the selected HTP application. Currently, in clinical practice the 3D patient model usually consists of tissues discriminated by a CT scan, such as muscle, fat, bone, lung and internal air [15]. With the development of automatic segmentation routines based on atlas registration or artificial intelligence (AI) algorithms, generating complex 3D models for the HTP purposes becomes feasible [15,16].

The purpose of this study was to test the application of an automatic AI segmentation routine for deep HTP purposes in the pelvic region. From publicly available CT scans, we created a 3D patient-specific 3D model using the automatic artificial intelligence based segmentation available in TotalSegmentator extension of 3D Slicer [19,20].

2. MATERIALS AND METHODS

2.1. SEGMENTATION OF THE CT IMAGES

First, we created a patient-specific 3D model from the series of the CT images available from the Cancer Imaging Archive [19,20]. The selected CT dataset
was for a pancreatic cancer patient. This patient data group has a bad prognosis as the symptoms often appear in the later stage. The tumour is also present in challenging locations for the radiotherapy treatment [22]. The CT images were imported into the 3D Slicer (version 5.2.2) for the AI segmentation for internal organs using the Total Segmentator extension [18]. Two segmentations, using the “Body” and the “Total” options were created and saved in the *.nrrd format. We used the “Total” segmentation option, since it contains individual organs, however without fat tissue. For fat assignment, we used the “Body” segmentation, which ensures that each CT pixel is assigned to a specific tissue. Afterwards, we combined these two segmentations and merged corresponding tissues, such as all muscle and bone parts, into a single file in the *.vtk format inside MATLAB (version 9.13, Natick, Massachusetts, USA) using the list shown in Table 3 in the Appendices. Then, we imported the CT images to the iSeg (version 3.10.57.98, Zürich MedTech, Switzerland) along with the MATLAB file and assigned individual organs. For fat tissue delineation, we used the “Body” AI segmentation inside the 3D Slicer and for muscle tissue, we used a threshold operation inside iSeg. Since Virtual Population models used for various in-silico studies, including those in hyperthermia field, contain cartilage, we manually segmented the cartilage as well [23]. Figure 1a) shows an example of the CT image and Figure 1b) the corresponding segmentation in iSeg. The whole process took 5 minutes of GPU computational time and 40 minutes of operational power from which the manual cartilage segmentation took 20 minutes.

2.2. HYPERTERMIA TREATMENT PLANNING SETUP

The selected HT applicator consisted of twelve 100 MHz dipole antennas placed in two rings within the 500 mm long elliptically-shaped shell with a width of 600 mm and a height of 500 mm. An elliptical shape was selected to obtain more uniform distance between the patient surface and the shell compared to a cylindrical setup. This 3D phased array system was positioned around the 3D model in order to place the target region (pancreas) into the centre of the applicator system and provide at least a 40 mm distance from the patient surface to the wire dipole antenna elements (Figure 2). We have selected pancreas as a target region in this study, which represents with respect to its shape and location, a challenging organ for the HT.

2.3. ELECTROMAGNETIC FIELD SIMULATION

A harmonic signal with 15 periods at 100 MHz was used for the excitation of all 12 antenna elements in the phased array setup. A 5 mm global discretisation FDTD step with a refinement to 2 mm for the region within the shell and to 1 mm for the wire dipole antenna was used. Absorbing UPML boundary conditions were placed 20 cm from the applicator model. The dielectric properties shown in Table 1 were assigned from the ITIS tissue database available in the Sim4Life package. All metallic parts were assigned as a perfect electric conductor (PEC) material. It took around 10 minutes to compute one EM field simulation accelerated by RTX 3080 Ti graphical processor unit.
Table 1. Dielectric properties at 100 MHz used in HTP [24, 25].

<table>
<thead>
<tr>
<th>Name</th>
<th>$\varepsilon_r$</th>
<th>$\rho$ [kg m$^{-3}$]</th>
<th>$\sigma$ [S m$^{-1}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>adrenal gland</td>
<td>64.2</td>
<td>1028</td>
<td>0.64</td>
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<td>air</td>
<td>1</td>
<td>1.2</td>
<td>0</td>
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<tr>
<td>blood vessel</td>
<td>76.8</td>
<td>1050</td>
<td>1.23</td>
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<tr>
<td>bone</td>
<td>15.28</td>
<td>1908</td>
<td>0.06</td>
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<td>cartilage</td>
<td>55.8</td>
<td>1100</td>
<td>0.47</td>
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<td>77.9</td>
<td>1040</td>
<td>0.9</td>
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<tr>
<td>fat</td>
<td>12.7</td>
<td>911</td>
<td>0.07</td>
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<tr>
<td>gallbladder</td>
<td>79</td>
<td>1071</td>
<td>1.01</td>
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<td>76.8</td>
<td>1050</td>
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<tr>
<td>kidney</td>
<td>98.1</td>
<td>1067</td>
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<td>large intestine</td>
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<td>69</td>
<td>1079</td>
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<td>lung</td>
<td>31.6</td>
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<td>66</td>
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<td>2</td>
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<td>1.66</td>
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<tr>
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<td>1089</td>
<td>0.8</td>
</tr>
<tr>
<td>stomach</td>
<td>77.9</td>
<td>1088</td>
<td>0.9</td>
</tr>
<tr>
<td>water</td>
<td>80</td>
<td>1000</td>
<td>0.002</td>
</tr>
</tbody>
</table>

2.4. Optimization and Evaluation

Individual EM field distributions were then imported to MATLAB for amplitude and phase optimisation of the antenna input signals using the particle swarm optimisation technique. We optimised the target to hot spot quotient (THQ) representing the ratio of averaged SAR inside the target region to the average SAR within the hotspot, which were assumed as a volume with 1% highest SAR outside the target region [26].

Aside from the THQ, we evaluated the SAR target coverages (TC) parameters TC25 (%) and TC50 (%), determining the volume of tumour coverage with 25% or 50% SAR iso-contour. We have compared two models,

• organs – for this model, we assumed a complete segmentation including internal organs,

• muscle – for this model, we assigned all internal organs (except lung) as a muscle and cartilage was split into bone structure and muscle using histogram threshold segmentation, which is currently the clinically applied segmentation strategy for patient-specific 3D models used in HTP.

We also computed the absolute THQ difference $|\Delta \text{THQ}|$ (%).

$$|\Delta \text{THQ}| = \left| \frac{(\text{THQ}_{\text{muscle}} - \text{THQ}_{\text{organs}})}{\text{THQ}_{\text{organs}}} \right| \times 100 \quad (1)$$

where $|\text{THQ}_{\text{muscle}}|$ is the THQ value obtained using muscle patient model and $|\text{THQ}_{\text{organs}}|$ value obtained from complete segmentation model including internal organs.

3. Results

The optimised power and phase coefficients of individual antenna input signals are shown in Table 2. Power coefficients are shown for 1 W of the total power of the phased array system.

Table 2. Optimised powers P [W] (normalised to 1 W of the total power) and phases $\Phi$ [°] of antenna input signals for organs and muscle segmentations.

For the complete segmentation model including internal organs, we obtained TC25 = 78%, TC50 = 6% and THQ = 0.63, while for the model with internal organs assigned as muscle, TC25 = 91%, TC50 = 46% and THQ = 0.71, the $|\Delta \text{THQ}| = 12.7%$. Figure 3 shows SAR cumulative histograms of the patient and pancreas for the detailed segmentation model including internal organs and for the patient-specific 3D model in which all internal organs were assigned as a muscle.

![Figure 3. SAR volume cumulative histograms of pancreas and whole patient model for complete segmentation model (organs) and for model with organs assigned as muscle (muscle).](image-url)
Figure 4. Normalized SAR CT overlay for complete segmentation model a) axial c) sagittal slices and for model in which internal organs were assigned as muscle b) axial and d) sagittal slices with highlighted pancreas contour in green.

Figure 4a) and Figure 4c) show axial and sagittal slices of the optimised SAR for the complete patient model while Figure 4b) and Figure 4d) show the patient-specific 3D model with muscle dielectric properties assigned to organs.

4. DISCUSSION

We have successfully integrated AI automatic segmentation into our overall HTP process in the pelvic region. It takes around 45 minutes to generate detailed patient-specific 3D models used in automatically generated HTP setups. We received difference of 13% for TC25 and 40% for TC50 between the detailed segmentation including internal organs and the model segmented into muscle, fat, lung, air and bone, which is currently standard practice in clinical HTP. These differences, observed in the challenging pancreatic region, highlight the importance of implementing the detailed segmentation in this region. However, even with the detailed segmentation, we obtained TC25 = 78%, which is considered to be sufficient (TC25 ≥ 75%) for the HT. We estimated that manually creating a complete segmentation model would take an experienced individual around ten hours, which is significantly more than the 45 minutes required for the AI-assisted segmentation. We expect that this time will be further reduced in near future, to 25 minutes, by adding an automatic segmentation of the cartilage.

The observed difference in THQ of 12.7% when comparing two studied models falls into a range of 7.0–22.8% difference found by VilasBoas-Ribeiro et al. [10] when comparing a clinical model containing muscle, fat, bone, lung and internal air and a very detailed model of the Virtual Population models. These models are commonly used for in-silico studies of EM field exposure, nevertheless they represent healthy models of healthy volunteers which led to the development of Erasmus Virtual Patient Repository (EVPR) created from CT scans of real HT patients [24]. However, the EVPR models consist of a limited amount of tissues, such as fat, muscle, bone, internal air and tumour. The implemented AI segmentation allows to conduct simulation studies including temperature and thermoradiotherapy modelling with realistic patient 3D models [28, 30]. These 3D models can be obtained from widely available public repositories, enabling non-clinical groups to also work in this area of research.

The optimised coefficients of antenna input signals differ between HTP results based on the muscle and organs segmentations. This was caused by different dielectric properties of individual organs with respect to muscle tissue. Tissue permittivity and conductivity influence the wavelength and attenuation of the propagating EM wave and thus also the optimised amplitudes and phases of individual antenna input signals. Predicting local areas with high temperatures (hot-spots), which usually appear at tissue interfaces with high dielectric contrast, might be improved with HTP based on a detailed segmentation. However, a study investigating whether a detailed segmentation leads to a higher EM dose within the target region and thus temperatures during the HT would need to be verified in clinical practice, which is outside the scope of this paper.

A total of 104 available tissues were segmented using the TotalSegmentator, which can also be used as constrained masks during the online optimisation of amplitudes and phases input signals of individual antennas in the phased array system. Detailed models also allow more accurate simulation guided design of HT devices using, for example, meta-material structures or compact antenna structures [31] [33]. Furthermore, this technology might also enable the creation of more complex anthropomorphic phantoms for hyperthermia quality control measurements including dielectric properties of specific phantom materials [34] [36]. In clinical practice, dielectric properties can be obtained individually for every patient using electric property tomography, which uses magnetic resonance imaging (MRI) scanner [57] [58]. MRI, along with Electric Impedance Tomography and Microwave Imaging, can be employed for non-invasive temperature monitoring during the HT, improving the overall treatment quality [39] [42].

5. CONCLUSION

The implementation of an AI segmentation routine to create patient-specific 3D models enables a more re-
alistic and tailored HTP approach that can be applied in clinical practice. This could extend the availability of HTP treatment guidance to more clinics, improving the overall quality of HT. Detailed models are also suitable for testing the accuracy of temperature tissue model predictions.

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REFERENCES


## A. APPENDICES

<table>
<thead>
<tr>
<th>Tissue name in HTP</th>
<th>Tissue name from TotalSegmentator</th>
</tr>
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<tbody>
<tr>
<td>adrenal gland</td>
<td>right_adrenal_gland, left_adrenal_gland</td>
</tr>
<tr>
<td>air</td>
<td>trachea</td>
</tr>
<tr>
<td>blood vessel</td>
<td>aorta, inferior_vena_cava, portal_vein, left_common_iliac_artery, right_common_iliac_artery, left_common_iliac_vein, right_common_iliac_vein</td>
</tr>
<tr>
<td>bone</td>
<td>L5_vertebra, L4_vertebra, L3_vertebra, L2_vertebra, L1_vertebra, T12_vertebra, T11_vertebra, T10_vertebra, T9_vertebra, T8_vertebra, T7_vertebra, T6_vertebra, T5_vertebra, T4_vertebra, T3_vertebra, T2_vertebra, T1_vertebra, C7_vertebra, C6_vertebra, C5_vertebra, C4_vertebra, C3_vertebra, C2_vertebra, C1_vertebra, left_rib_1, left_rib_2, left_rib_3, left_rib_4, left_rib_5, left_rib_6, left_rib_7, left_rib_8, left_rib_9, left_rib_10, left_rib_11, left_rib_12, right_rib_1, right_rib_2, right_rib_3, right_rib_4, right_rib_5, right_rib_6, right_rib_7, right_rib_8, right_rib_9, right_rib_10, right_rib_11, right_rib_12, left_humerus, right_humerus, left_scapula, right_scapula, left_clavicle, right_clavicle, left_femur, right_femur, left_hip, right_hip, Sacrum</td>
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<td>esophagus</td>
<td>esophagus</td>
</tr>
<tr>
<td>fat</td>
<td>body</td>
</tr>
<tr>
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</tr>
<tr>
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<td>heart, left_atrium, left_ventricle_of_heart, right_atrium, right_ventricle_of_heart, pulmonary_artery</td>
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<tr>
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</table>

**Table 3.** Merging tissues from TotalSegmentator and its corresponding tissue names in HTP models.