

Response to “ Comments on ‘ Novel real-time tumor-contouring method using deep learning to prevent mistracking in X-ray fluoroscopy ” ’

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1 Title:

2 Response to “Comments on ‘Novel real-time tumor-contouring method using deep learning to
3 prevent mistracking in X-ray fluoroscopy’”

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14 To the editor,

15 We would like to respond to the comments of Drs. Mori and Endo [1] on our research paper [2].

16 First, we wish to discuss their suggestion on the requirement for using actual fluoroscopic images in
17 the test stage. The necessity to validate our method using clinical fluoroscopic imaging was already
18 mentioned in the Abstract, Discussion, and Conclusion sections [2]. The sentences in the Discussion
19 section include the following: “We understand that our results were obtained from preliminary
20 simulated fluoroscopic images, and we must validate this method using real clinical fluoroscopy. The
21 anticipated primary difficulty is the different image qualities between the DRRs and the clinical
22 fluoroscopy images. However, we expect that this problem can be solved by improving the DRR
23 quality to be similar to the quality of clinical fluoroscopy images, or by creating a wide contrast
24 variation in the training images for the input dataset of deep learning” [2]. The last sentence might be
25 too optimistic; however, this was because we had already confirmed a successful result using clinical
26 fluoroscopic imaging. Our next report will demonstrate the feasibility of our method using clinical
27 fluoroscopic imaging.

28 We also wish to discuss their concern that the superior results were obtained as a result of overfitting,
29 because training images were similar to the test images. We demonstrated the advantages of our
30 method using geometric and simulated fluoroscopic models [2]. In the geometric model, the
31 probability of matching a training image to a test image was almost zero. Therefore, it was proven that

32 the good tracking results were not caused by overfitting. In the simulated fluoroscopic model, we
33 already mentioned that the possibility of matching a training image to a test image was 1 in 400. This
34 low value does not directly mean that there was overfitting, because deep learning can be considered
35 a statistical parameter optimization method. This is completely different from a template matching
36 method using a dictionary file [3]. In addition, in deep learning, “data augmentation” in and of itself
37 is well known to be one of the techniques for reducing overfitting. Famous data augmentation methods
38 are affine transformation and adding noise to training images. Although a uniform noise is generally
39 used, some reports selected a randomly arranged nonuniform pattern and demonstrated improvements
40 in accuracy [4, 5]. Our data augmentation method is similar to that in these reports because the
41 overlapped bone structure can be regarded as a nonuniform pattern. Our superior results were therefore
42 not caused by overfitting, contrary to their concern.

43 Other minor questions: It was not surprising that the amplitude of the tracking error was less than the
44 pixel size of the simulation image because the tumor position was calculated as the centroid by many
45 pixels, which identified the tumor region using our image segmentation method. This was simply a
46 statistical effect. It was also not surprising that our tracking error was less than that of other methods
47 because other methods included some additional errors such as the identification of a ground truth
48 position of tumors manually.

49 Finally, we wish to discuss their suggestion that we need to change the title of our report based on
50 their concern that the title could mislead RPT readers into believing that our study was performed with
51 actual fluoroscopic images. This suggestion cannot be accepted. The appropriateness of the title was
52 already judged by an editor and referees. In the Abstract [2], we clearly stated, “Our results from a
53 simulated fluoroscopy model showed ...” and “Further studies using clinical fluoroscopy are highly
54 anticipated.” Moreover, in our paper [2], the subsection titles in the Methods and Results have
55 highlighted the use of “Simulated fluoroscopy model.” We therefore think that their concern is
56 unfounded. This is also supported by the fact that an article, which was submitted before their
57 comment, cited our paper correctly as “They validated their method on simulated fluoroscopic images”
58 [6].

59

60 **Compliance with ethical standard**

61 **Conflicts of interest**

62 The authors declare that they have no conflicts of interest.

63 **Ethical statement**

64 This article does not contain any studies performed on human participants and animals.

65

66 **Reference**

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68 learning to prevent mistracking in X-ray fluoroscopy” by Terunuma et al. Radiol Phys
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