Registration and fusion of 3D surface data from CT and ToF camera for position verification in radiotherapy

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Abstract

The purpose of this study is to introduce a low-cost method for verification of patient positioning before and during irradiation in radiotherapy. The experiments strategy is implemented by using a phantom like a human head in two modes: with and without thermoplastic masks. Radiotherapy is an effective clinical option for topical tumors treatment. Ability to the monitoring and control the patient's position during treatment is among the important items in radiotherapy. We registered to modality of 3D surface image in point cloud format, dynamic 3D image of time-of-flight camera (includes outer shape of head) and static 3D image of CT slice sectional by coherent point drift algorithm. Accuracy of 3D surface registration was calculated by average symmetrical surface distances (ASD) that it is a new method based on surface distance. The mean ASD calculated for rotation around X and Y axes of phantom is 2.62 ± 0.97 mm with immobilized thermoplastic mask and accuracy be increased to 1.69 ± 0.88 mm in non-thermoplastic mode. By performing paired *T* tests for ASDs, it was found that the use of a thermoplastic mask does not make a significant difference in the data acquisition. By developing this research to image fusion of that's 3D data sets, we will design to augmented reality in radiotherapy for verification of treatment planning and compare it with the electronic portal imaging device.

Keywords Radiotherapy · Verification · Patient positioning · 3D surface registration · Image fusion

1 Introduction

Radiotherapy is an effective clinical option for topical tumors treatment. The prescribed dose is used by the patient gradually over the several days. Therefore, the daily patient's set-up accurate has a significant effect on the effectiveness of the treatment. The ability to correction and realignment the patient's position in radiotherapy devices (such as linear accelerators), as well as ability to the monitoring and control the patient's position during treatment (irradiation) are among the important items in radiotherapy. By analysis of natural patient movements during the treatments and subsequently, irradiation plan

can be modified based on these movements. The access to position information and movement of internal organs and bones during the irradiation (treatment) are very limited. However, different equipment is designed for this purpose. This equipment is divided into two categories: two-dimensional (2D) and three-dimensional (3D). Portal images (or electronic portal imaging device: EPID) are used to do this action through two-dimensional images; these images are the result of radiation in the treatment position on film or a suitable sensor (intensifier). Unfortunately, these images have a low contrast due to the high radiation energy used, unlike the X-ray images [1]. However, due to the high cost of the EPID system or the use of an

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old irradiation machine, many radiotherapy centers do not have any devices to patient's position verification.

Before applying the treatment, the patient's position on the irradiation couch is aligned with what is at the treatment simulator center (on CT simulator). This operation is aimed at uniformizing the patient's condition in treatment and simulation. Immobilization methods and fiducial marking on the skin are techniques which are used along with portal images to enhance and improve the accuracy of patient's setup [2]. Patient immobilization technique, as it is done with thermoplastic masks, cannot not be a serious obstacle to changes any daily shape in the patient's body surface or outer tissues. The marks which are invasively implanted in the patients' body surface with surgery, in addition to high costs and the possibility of movement in the body, cause problems when portal imaging is used to confirm patient set-up. Data collection from displacement and changing the tumor position by simulators or CT imaging is one of the measures included in the conformal treatment plans [3]. In conventional method by EPID, the mentioned displacements are mainly identified and evaluated in 2D plan. AlignRT (VisionRT Ltd., London, UK) [4] and OSMS (Optical Surveillance Monitoring System, Varian Medical Systems, Inc., Palo Alto, CA, USA) [5] are new systems for evaluating the 3D patient positioning. However, these devices (like EPID System) are very high-priced and some of them can provide real-time performance for continuous monitoring of body surfaces.

An optimal approach for patient positioning and monitoring is the installation of ToF camera with optical 3D surface imaging capability for treatment machines (i.e. accelerators) and treatment planning devices (i.e. CT simulators). Fast 3D acquisition data from the patient's body surface makes it possible the clinical use of ToF cameras even during the irradiation. Therefore, 3D surface data obtained from the patient's body during the irradiation is compared with similar surface data that was previously collected by CT simulator for verification of the patient positioning [6, 7].

In the last few years, the gaming industry has introduced innovative low cost depth camera technology. These low-cost cameras (< 200\$) have been launched primarily for entertainment and gaming applications, although several medical applications have been explored by researchers. The Microsoft Kinect is used as an example of a low-cost consumer grade 3D depth camera for capturing and analyzing external organs motion.

Considering the patient's body as a rigid frame is almost impossible; for this reason, the research is implemented in the head and neck for simplicity and ease. It is investigated the patient's position for radiotherapy, considering the angles and the field size of irradiation, the size of the tumor and the location of sensitive tissues around the

tumor is provided in the center of treatment simulator by treatment planning process. The patient's position in this condition is called "the initial" setup. Head and neck cancer (HNC) patients are often immobilized in a fixed position with custom-made thermoplastic masks. As the first step at treatment center before irradiation, to increase the accuracy of tumor targeting, It is attempted to setup the patient's position in conditions similar to the initial setup by aligning the surface landmarks (i.e., tattoos), which placed on the patient's body during simulation through movement of the treatment couch. Verification of patient positioning is one of the important processes in radiotherapy sessions before irradiation [8–10]. In clinical operations, the displacement error of the patient's position (or in other words the precision in targeting the tumor) is allowed in less than 2 mm [7].

Not only the natural movements of the body in a short time, but also the changes and movements that occur in the long term in the patient's body should be considered from one treatment session to another, because one treatment period usually takes several weeks. This obviously causes errors in evaluation and comparison of the surface data. In conventional method by EPID, a portal image be detected the errors only in x and y axes. So, in order to detect an error in the z direction, we need to provide another orthogonal image. While all three-direction errors are detected with a 3D image by the ToF camera through only one projection. That means the ToF cameras also have the ability to detect motion in the direction vertical to the projection plane of the portal image, while in one portal image (alone) this important issue cannot be detected.

In the proposed method of the study, we will fusion two categories of datasets. One datasets is 3D surface image from the patient's body which registered by CT Simulator before the irradiation and another is 3D image data from the body surface acquisition during irradiation by the ToF camera. Then the tumor position and its displacement are evaluated in terms of information obtained from the data surface of the patient's body by fusion of these datasets. Therefore, the patient's position verification before irradiation and the error measurement in the tumor targeting and the measurement of displacement (patient or tumor) during irradiation will be the outcome of the research. In other words, monitoring a patient's position will be possible in real time. Thus, our aim is to introduce a low-cost method for verification of patient positioning before and during irradiation for use in radiotherapy centers without an EPID or any verification positioning systems.

Effective data registration is very important in the processes of the medical field. One of the most common methods of 3D surface registration obtained from images of CT and ToF camera is aligning the landmarks that can be detected in those surface images. These landmarks

are divided into two categories: artificial and anatomical. Artificial landmarks are considered as the gold standard method rather than the others' verification of image registration, but require additional and sometimes non-trivial surgery on the patient [11]. There are some difficulties for registration due to the small size of the landmarks' dimensions. For example, there are variations in the identified locations of the landmarks on the patient, as well as some difficulty in identifying exactly the same locations within the patient's three-dimensional (3D) image. Therefore, there are new approaches to use the anatomical landmarks such as the nasal tip and the inner or outer corners of the eyes, although they may not be accurate [12].

In addition, marker-based registration is a time-consuming process, with too much user interaction, which is a major defect discouraging the popularity of patient positioning. Therefore, the process of markerless registration has become increasingly popular [13].

Maurer et al. [14] have invented a markerless registration method that works using a probe and movement on the skin, some points were selected on the patient's body surface, and determine the best matching of this patient's point-cloud to the surface extracted from the patient's 3D image. In this method, there was no need to find landmarks for registration between the 3D images and patient's body surface. Unfortunately, this method was time-consuming and was subjective to intra- and inter-observer variations. Recently, the use of optical techniques has been developed for 3D positioning in the field of radiotherapy, and many articles on this subject have been published in the field of medical imaging applications [15–17]. In 2007, Konietzschke et al. [18] introduced a markerless registration non-contact method using DLR 3D-Modeller (3DMo). Nicolau et al. [19] also proposed a system to reconstruct the patient's abdomen, and then registered it to pre-operative images from the same area with iterative closest point (ICP) method to guide percutaneous punctures in interventional radiology. Reuben et al. [20] used a fast 3D surface scanner to obtain 3D image of the patient's face and aligned it with pre-prepared MR or CT head images. Schaller et al. [21] and Placht et al. [22] introduced ToF-based systems for auto-setup of the patient in abdominal radiotherapy using ICP method. A system for tracking the head movement was provided with 3D imaging of the brain by Olesen et al. [23].

According to what mentioned, the systems require sophisticated operation, a lot of time to setup and installation or needs special equipment. On the other hand, there are some systems that can be used in the treatment room [24, 25] and have proved to be promising clinical applications. However, due to increasing the burden on the radiotherapists (or physicist) and need much interaction of the above systems with the operator, the users are

not satisfied with the use of IGRT systems. Bauer et al. [26] introduced a method for surface image registration from two different system imaging that enables to align the data directly from intra-fractional structured light into a reference image obtained from the pre-fractional tomographic planning data.

Our proposed method is not only low-cost but also a type of 3D surface registration without any additional tools and easy to use. The AlignRT is the conventional system in radiotherapy center that used to 3D patient positioning. When the system is in real-time mode, the surface image capture speed of the patient's body is about 0.1 to 0.3 frames per second (fps). Peng et al. [27] have reported a mean registration error of 1.2 ± 0.7 mm (mean $\pm$ standard deviation) for translational displacement and an error of approximately $0.7^\circ \pm 0.4^\circ$ in the rotational component of the AlignRT system using a phantom head and neck.

We used a new version of Microsoft Kinect called time-of-flight, which is more accurate than the old version. In the proposed method, two 3D surface images, one taken from CT Simulator and the other taken from the ToF camera and then those data register on each other. Markerless registration will be achieved by CPD technique. Finally, we will evaluate the accuracy of the registration by defining a new criterion called ASD (average symmetrical surface distances) [10, 28, 29].

Our research team has previously reported the results of the motion analysis. That results show that for rigid head and neck phantom it is possible to obtain an accuracy of 1.40 ± 0.65 mm and $0.15^\circ \pm 0.07^\circ$ for translations and rotations respectively [30].

2 Materials and methods

Searching the points with specific feature in a region of image and matching them to corresponding points in other images is a key component of machine vision in 2D and 3D domains. The registration, object recognition, scene reconstruction, or similarity search in databases are the topics discussed in this field. 3D registration is the subject we will focus on in this study. One common method for aligning two or more sets of points or surfaces is CPD (Coherent Point Drift) algorithm. Follow details of this method in reference number [31].

CPD technique has a wide range of applications such as image registration, target recognition, computer vision, image retrieval and classification and the mobile robot. Registration in this technique is usually divided into two rigid or non-rigid groups. In CPD registration technique, the principle is to find a connection between two sets of points that will result in the definition of a transform relationship between two sets. Since two sets

of points are taken from different imaging equipment, different imaging angle and different time or conditions and illumination, therefore, the resulting transform relationship for registration between two sets of points is not always valid. The existence of something's such as deformation, noise and outliers bring point-to-point registration into a very serious problem [32].

Compared to other point set registration algorithms, such as ICP [33] or scale invariant feature transform (SIFT) [34], CPD has higher registration precision not only for the rigid registration but also for the non-rigid. In CPD, the corresponding relationship between two sets of points is performed by expectation maximization (EM) algorithm. The action of EM algorithm is iteration minimizing the expectation of the negative log-likelihood function.

In fact, CPD is considered alignment of these two sets of points as the probability density estimation problem; considering the one of set points as the Gaussian mix model (GMM) centroids and the other as data points. We register GMM centroids to data points, by maximizing likelihood estimation. In optimal mode, the set of aligned points and their correspondences are obtained using posterior probability of GMM components. CPD ability is that makes GMM centroids to move logically as a group to keep the topological structure of the set of points be maintained.

The proposed framework is capable of reducing the ToF measurement noise by means of distance calibration and temporal Kalman filtering of the distance data. After these preprocessing steps, a pair of surface datasets is matched using a rigid transformation allows only for translation, rotation and scaling invariant features are used for pre-registration, followed by CPD algorithm [35].

An overview of the processing pipeline is shown in Fig. 1. The input consists of two datasets denoted as a dynamic ToF camera dataset (acquired, e.g., during daily treatment delivery) and a static surface dataset from CT (acquired, e.g., in the CT simulator of treatment planning system). In this work, we have used only point clouds data inputs. Before the ToF datasets are registered, the data quality is improved by applying a distance correction followed by Kalman filtering [36]. Furthermore, temporal surface of phantom (or patient) is separated in a feature

extraction step. 3D surface segmentation step, made 3D shape of outer CT layer from CT slice's [37].

Quantum noise decreases in distance data through Kalman filtering. Unlike conventional noise removal techniques (e.g., median filtering or a filter with finite impulse response), The Kalman filter belongs to the prediction filter class. However, the Kelman filter is considered desirable as a linear filtering, if the input data is distributed with white and Gaussian noise. With this technique, we are able to reduce the distance noise, while keeping movement possible, with very little delay. In our Kalman filtering step, we obtain a distance pixel data processing time based on a two-dimensional measurement noise model, which depends on amplitude and distance values. We use a 3D state vector that includes the current distance, speed, and current acceleration (first and second derivatives of the distance) [38].

In our analysis of the ToF camera, we could measure approximately white, Gaussian noise in the raw distance values provided by the camera. So, coupled together with the time-domain filtering which is native to prediction filters, makes Kalman filtering particularly well-suited for this application. The low delay plays a key role in real-time applications, such as gating/tracking, which requires a fast dynamic response of the system.

For reducing systematic errors, some corrections are made to the values of each pixel as default, in order to improve spatial accuracy in detecting the depth intervals. These depth corrections are independent of the final position of the camera in the treatment room. However, it is important to note that the choice of calibrated distance range (from 0.8 to 1.2 m, in this research) for ToF camera will be approximately the same as the condition in the treatment room. The distance between camera and patient will be in this range. The eight large boards with different infrared reflectivity were used at three distances of 0.8, 1.0, and 1.2 meters with a fixed integration time. The systematic errors for each pixel are calculated based on the difference between the depths measured with the actual distance (distance the table to ToF camera). Then those distance offsets is stored as a look-up table depending on the three distances, for each pixel based on the intervals and intensity [39].

Fig. 1 Processing pipeline of registration framework

Set up two sets of points: we define the CT data point set as $Y_{M \times D} = (y_1, \dots, y_M)^T$, and the ToF data point set as $X_{N \times D} = (x_1, \dots, x_N)^T$, M, N represent the number of points, D is the dimensions of the point set. We defines an uniform distribution as $p(y|m+1) = \frac{1}{M}$, the weight is ω ($0 \leq \omega \leq 1$). And the probabilities $P(m) = \frac{1}{M}$ for all GMM components. So we get the weighted GMM probability density function [31]. And to see [1]:

$$p(x) = \omega \frac{1}{N} + (1 - \omega) \sum_{m=1}^{M+1} \frac{1}{M} p(x|m) \quad (1)$$

$$\text{where: } p(x|m) = \frac{1}{(2\pi\sigma^2)^{D/2}} \exp\left(-\frac{x_N - y_M^2}{2\sigma^2}\right).$$

In registration process, when the CT data point set geometry transformation, σ^2 is also changing. Through the covariance analysis, we consider that larger value of σ^2 show that multiple points in the CT data point set corresponding to a point in the ToF data point set. In order to find a one-to-one relationship, σ^2 must be infinitely close to a minimum. So, to align the two point sets: CT data (y) and ToF data (x), a transformation T_p (translation, rotation and scaling) must be found by CPD algorithm.

$$x = T_p(y_m : R, t, s) = sRy_m + t \quad (2)$$

where $R_{D \times D}$ is a rotation matrix, $t_{D \times 1}$ is a translation vector and s is a scaling parameter. Since the CT and the ToF data's, respectively "y" and "x" information, contain tens of thousands of dots (points), the speed is low to align these two point sets directly. Therefore, instead of using 3D data plan, a 2D format was used in order to improve efficiency in the process of registration. In this structure, each pixel of 2D data contains the depth information of that pixel.

The proposed framework in this study consists of three steps: The first, topical topology of the upper face (such as the nose, eyes, lips and cheeks) of the CT(y) and ToF(x) datasets are segmented from owns 3D image information. Considering the distinct imaging modalities in creating data sets and the differences in CT coordinate system and ToF camera is important in this step. Also, the treatment room light and ToF camera angle affect the number of points in the ToF image. The second, the establishment of a sustained geometric relationship using CPD algorithm for optimal registration between the segmented parts of the two data sets and generating the corresponding conversion function (T_p). The best registration of two datasets occurred in our experiments with $\omega = 0.7$.

Depending on the structure of the ToF camera, If the object is closer, the point density will be much higher. Since these two data sets contain tens of thousands of dots, in order to increase the speed of registration, we

reduce the number of points in the range from 1500 to 2000 points. To do this action, all the points in the 1 mm^3 voxel size are referenced to its center by using a 3D filter. The third and last, CT and ToF datasets fuse by applying the conversion function (T_p) obtained from the previous step. In this step, according to the coordinate system of the treatment couch, the information of both datasets (CT including internal organs and ToF including external organs) will be displayed at the same time for evaluation of the target (tumor) position before or during radiotherapy [40, 41].

In other words, with comparing the initial setup (which is stored in the simulation step of treatment, or the first treatment session) and the setup in next sessions (or during live treatment), the displacements can be measured in order to correct it (if irradiation does not start), even a more accurate estimate of deliver dose to tumor will be possible (if the displacement occurs during irradiation). A new surface distance based method is proposed to evaluate the quality and accuracy of the registration. Therefore, we first introduce ASD (average symmetrical surface distance) [42]:

$$ASD(x, y) = \frac{1}{\sum S_x + \sum S_y} \left(\sum_{S_y \in S(y)} d((S_y, S(x))) + \sum_{S_x \in S(x)} d((S_x, S(y))) \right) \quad (3)$$

where, $S(x)$ and $S(y)$ represent the surface datasets of ToF and CT, respectively. S_x, S_y are desired points of the surfaces $S(x)$ and $S(y)$, respectively. The "d" operator is used to express the amount of Euclidean shortest distance between one point and another surface. Since the information obtained from ToF does not provide a perfectly smooth surface image, this surface is basically not ideal (not very smooth and there are not data related to marginal regions), therefore, the ASD of all points does not correctly indicate the accuracy and quality of the registration (ASD may be very large for regions that do not contain data). Thus, we use points in the regions of interest (including nose, lips, eyes, and cheeks) to calculate ASD, instead of all points of the surface, where these regions are in fact represents the main features of the face.

Then, we propose to obtain the histogram distribution H of the $d\{[S_y, S(x)]\}$:

$$H(d(i)) = \sum_{x_{i-1}}^{x_i} d((S_y, S(x))) | d((S_y, S(x))) \in (x_i, x_{i-1}) \quad (4)$$

where, H reflects the accuracy of registration. The greater proportion of low value in H means the closer of two point sets, which indicates a better registration result. Therefore, the more points distribute within the low area means a better registration result [43].

The ToF camera has been mounted on the head of accelerator Gantry and in front of the treatment couch. The camera observed a region of the treatment couch in front of Gantry with an angle of approximately 10 degrees at a mean working distance of 100 cm (Fig. 2). Due to limitations in the treatment room, the mean distance and angle of the camera during evaluation and data acquisition has not been changed. As well as, Fig. 2 shows, a phantom in shape of a human head, and the thermoplastic mask to immobilize it are used to facilitate the implementation of the test and the feasibility of researching for clinical applications. The phantom immobilizes on the couch and ToF camera will be rotated around the couch along with Gantry (Fig. 3). Therefore, ToF image is taken by camera from the phantom in the range of $\pm 40^\circ$ from the vertical axis, through rotation of Gantry. In this range, we have a nearly complete image of the upper phantom surface, including nose, cheeks, lips and eyes. In this way, it is possible to observe the phantom in various views and evaluate

the robustness of the proposed method and its results. The accuracy of Gantry rotation is 1° and the accuracy of couch motion is 1 mm for each of the three translation parameters. The test is performed with rotating and imaging ToF camera around the Y and X axes of patient's couch (as shown in Fig. 4). To run the rotation around the x-axis, at first the treatment couch is placed in 90° , relative to the standard position then, as shown in Fig. 4, the rotation around X-axis is available.

ToF camera capture surface image of phantom in each position of the Gantry (angle from the vertical axis) then, the upper layer of the surface image (the ROI area) is segmented afterwards with the same surface data from 3D CT image, the registration is done by CPD algorithm. The Mimics software is used to create 3D image from CT layers images and the upper surface of the 3D image (the ROI area) has been segmented in the point cloud format with the same software. The registration evolution will be performed by calculating ASD at each ToF imaging

Fig. 2 ToF placement at a distance of 70 cm and 10° at the head of gantry and Image of phantom and thermoplastic mask used for the experiment

Fig. 3 Image of phantom with thermoplastic mask on CT simulator couch

Fig. 4 Rotate the Gantry and ToF camera to achieve different surface image of phantom. Left: 20° rotate around Y axis of patient. Right: -20° rotate around X axis of patient

angle. To complete the evaluation and detection of effective errors in registration and discussing about the results of ASD, the implementation operations are done in two modes: The first step, the phantom immobilizes with thermoplastic mask on the treatment couch and in the second step will be used the phantom alone without thermoplastic mask. In the second step phantom is fixed on the couch and does not move during the test run. In Figs. 5 and 6, we show 3D image reconstructed from sectional images of CT simulator by MIMICS software and

its surfaces segmented to registration 3D image of ToF camera. Also in Figs. 7 and 8 be shown the segmented surface of 3D image from ToF.

The CT images were acquired using SIEMENS SOMATOM CT simulator (Fig. 4); meanwhile data surface from CT layers images was segmented by MIMICS software. The distance correction and filtering module is implemented in C++, and the 3D segmentation and registration modules and ASD computing are achieved with Matlab software.

Fig. 5 3D Image from CT layers of phantom without thermoplastic mask reconstructed by MIMICS and segmentation of its upper surface

Fig. 6 3D Image from CT layers of phantom with thermoplastic mask reconstructed by MIMICS and segmentation of its upper surface

Fig. 7 3D Image of phantom without thermoplastic mask captured by ToF camera and segmentation of its upper surface

Fig. 8 3D Image of phantom with thermoplastic mask captured by ToF camera and segmentation of its upper surface

3 Results

We aimed to fusion the head's CT data to the face's ToF data via 3D surface registration of those datasets. In order to evaluate the accuracy of 3D surface registration for positioning of radiotherapy HNC patients by ToF camera, we have registered the ToF dataset to the phantom's CT surface at two conditions: the first step is done by phantom with thermoplastic mask, and the next step without thermoplastic mask. In each condition, a 3D surface image of the phantom has been taken by ToF camera, and then we calculate *ASD* after fusion of two data sets: head's CT and face's ToF. In order to ensure the robustness of our method, we repeat that procedure at different angles of ToF camera relative to the vertical direction. For this purpose the camera is fixed on

Gantry and it rotate like Gantry around the phantom. At this stage we have tilted the camera $\pm 10^\circ$, $\pm 20^\circ$, $\pm 30^\circ$ and $\pm 40^\circ$, relative to the vertical direction.

Histogram distribution are showed in Figs. 9, 10, 11 and 12 which represents the registration result in the regions of interest, in which the horizontal axis represents the value of *ASD* (mm) and the vertical axis represents the number of points located within the range of the horizontal axis. There are more points distributed within the low area, which means a good registration result. Note that, in Figs. 9 and 10 that phantom with thermoplastic mask used to fusion surface images about 87% points distributed within range 0–3.5 mm while in Figs. 11 and 12 (in condition of without thermoplastic mask), the same distribution of points has happened within range 0–2 mm, this difference is due to the surface of thermoplastic mask and the holes on it.

Fig. 9 Histogram distribution of ASD calculated from ToF surface image by rotation around Y axis, phantom with mask

Fig. 10 Histogram distribution of ASD calculated from ToF surface image by rotation around X axis, phantom with mask

Fig. 11 Histogram distribution of ASD calculated from ToF surface image by rotation around Y axis, phantom without mask

As shown in Table 1, the average of ASD calculated for rotation around X and Y axes with thermoplastic mask on phantom is 2.62 ± 0.97 mm (maximum is 2.66 ± 0.98 mm and minimum is 2.57 ± 0.96 mm) and when we repeat the experiment without thermoplastic mask, better results are obtained at 1.69 ± 0.88 mm (maximum is 1.70 ± 0.89 mm and minimum is 1.69 ± 0.88 mm). Due to the accuracy

required in clinical operation (If the patient's displacement error is less than 2 mm, it is acceptable) and compared to the results of the AlignRT system that is mentioned in the introduction section, thus these means getting good results to fusion of two data sets: head's CT and face's ToF.

According to the data in Table 1, we have performed paired T-tests to compare mean ASD in four conditions:

Fig. 12 Histogram distribution of ASD calculated from ToF surface image by rotation around X axis, phantom without mask

Table 1 ASD for rotation around X and Y axes

Rotation (°)	Rotation around Y axis				Rotation around X axis			
	With mask		Without mask		With mask		Without mask	
	Mean ASD (mm)	± SD (mm)	Mean ASD (mm)	± SD (mm)	Mean ASD (mm)	± SD (mm)	Mean ASD (mm)	± SD (mm)
−40°	2.51	0.91	1.56	0.73	2.59	0.84	1.59	0.73
−30°	2.55	0.99	1.63	0.77	2.67	0.99	1.66	0.77
−20°	2.57	0.98	1.69	0.82	2.57	1.06	1.69	0.83
−10°	2.56	0.94	1.69	0.86	2.62	1.01	1.65	0.82
0	2.55	0.94	1.58	0.82	2.80	0.95	1.66	0.90
10°	2.56	0.93	1.82	1.10	2.64	1.01	1.73	1.03
20°	2.61	0.98	1.85	1.01	2.64	1.12	1.76	0.98
30°	2.58	0.98	1.81	1.00	2.78	1.00	1.76	0.96
40°	2.61	1.03	1.66	0.88	2.63	0.83	1.70	0.88
Total mean ASD	2.57		1.70		2.66		1.69	
Total mean SD	0.96		0.89		0.98		0.88	

In the worst condition, the calculations of the average ASD, based on the rotation around the Y and X axes of the phantom with and without thermoplastic mask achieved 2.78 ± 1.00 mm and 1.85 ± 1.01 mm, respectively

- $T_1 = 0.029$ ($p_1 = 0.67$); compare mean ASD, in rotation around Y axis with mask and without it.
- $T_2 = 0.025$ ($p_2 = 0.72$); compare mean ASD, in rotation around X axis with mask and without it.
- $T_3 = 0.020$ ($p_3 = 0.76$); compare mean ASD, with mask in rotation around X and Y axes.
- $T_4 = 0.034$ ($p_4 = 0.54$); compare mean ASD, without mask in rotation around X and Y axes.

Therefore, since both p_1 and p_2 are larger than 0.05, there is no significant difference between the two groups in the use of the mask. On the other hand, both p_3 and p_4 are larger than 0.05, thus there is no significant difference between the two groups in the rotation around x and y.

4 Discussion

We have provided and evaluated a practical system based on registration of surface images obtained from CT and ToF camera in medical applications, with a particular focus on radiotherapy to detect the precise targeting of the tumor before irradiation. Fusion of two imaging systems in this study allows simultaneous display of the internal organs and external surfaces of the patient's body. ToF camera calibration process before imaging and using Kalman filtering on the data acquisition from ToF camera will increase the accuracy of calculation and reduce the errors to the registration of images. Furthermore, the use of CPD technique for

registering 3D–3D surface datasets on point cloud format that it was a very accurate initialization for the subsequent optimization. Different coordinate systems in CT and ToF 3D images should be considered when fusing images. Also, reducing the number of dots in the point clouds images in order to increase the speed of registration should be to a level that does not reduce the quality of the fusion of images. According to the ToF range (≥ 0.5 m), the nearest patient distance to the ToF camera should not be less than this. The introduction of ASD as an index for assessing registration is used for surface datasets. In the worst condition, the calculations of the average ASD, based on the rotation around the Y and X axes of the phantom with and without thermoplastic mask achieved 2.78 ± 1.00 mm and 1.85 ± 1.01 mm, respectively. In fact, the output of this study is introduction of a simple, low cost, and accurate method for the verification patient positioning before irradiation. The development of this system as one of the augmented reality applications in the field of radiotherapy for verification of treatment planning and compare it with the EPID, is one of the team's future plans. As future work, we can use some existing fusion and information processing techniques in image processing as combined with our practical approaches in order to develop the imaging system.

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Conflicts of interest The authors declare that they have no competing interests.

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