Single Marker Localization for Automatic Patient Registration in Interventional Radiology

Michael Tschannen, Grzegorz Toporek, Daphné Wallach, Matthias Peterhans, Stefan Weber

ARTORG Center for Biomedical Engineering Research, University of Berne, Switzerland

Contact: grzegorz.toporek@artorg.unibe.ch

Abstract:

Accurate definition of single marker (SM) locations in computed tomography (CT) images is a part of the patient-to-image registration technique used in our navigation system for interventional radiology. The SMs are currently selected manually by the user. We herein present a two-step image processing algorithm first uses morphological operations on the binarized CT image for volume of interest (VOI) extraction and then applies a Hough transform (HT) to precisely localize SM centers in VOIs. This leads to fully automatic SM localization with precision that exceeds manual localization.

Keywords: single marker localization, automatic patient registration, interventional radiology

1 Problem

CAS-One IR (CAScination, Switzerland, Bern) is a navigation system for interventional radiology. It can be used for trajectory planning and navigation based on CT images in percutaneous liver tumor ablation among other applications. The system uses optical tracking for tool localization and patient registration. Six sterile, optical single markers (SM) (Atesos GmbH, Switzerland), are attached to the patient skin in the region of the target organ before the CT scan is performed (Fig. 1). After the scan, the SMs are defined in the image data and the positions measurements in the patient coordinate system are obtained from the Vicra tracking camera [6]. Using these measurements, patient-to-image registration is achieved and the real-time measurements from the camera enable detection of patient motion and deformation.

With the current workflow, the user of the system has to manually select the SM centers in the CT image, using a single view (transversal) CT image viewer. This procedure is time-consuming and represents a source of error (fiducial localization error FLE) which directly affects navigation accuracy. Furthermore, it represents the system's only non-automatized step in patient registration. The aim of the work presented in this paper is to develop an algorithm for fully automatic detection of the SM centers in the CT image, such that the time needed for localization is reduced as well as the localization precision is increased compared to the manual method. As far as we know, there is no prior work on the automatic localization of this special type of single, reflective marker, and thus we consider this work to be novel in the field of automatic marker localization.

Since the SM materials have densities similar to human tissue, they cannot be distinguished from the body in the CT image by applying level-windowing and intensity threshold operations (as usually done for localizing Beekly spots or other radiopaque markers [7]). When looking at the CT image of the SM (Fig. 2), it can be seen that the reflective marker sphere itself appears as a partially open sphere with a slightly higher intensity as the rest of the marker. The transparent shell enclosing the SM has lower density and is less spherical. Existing works such as [1] suggest using Hough transfrom (HT) to detect and localize parameterized geometric shapes such as spheres in medical images. Other works like [8], [9] suggest using template-based matching to determine the position and orientation of markers. In the present problem, only the position of the SM sphere center is required and therefore template-based matching would compute unnecessary information (orientation). Moreover, high reliability as well as low variability is essential and is in our opinion provided by the HT algorithm rather than template-based matching. As the inner reflective sphere of the SM has known diameter and is more spherical than the outer shell, spherical HT can be used to precisely compute SM locations. Since applying HT on the entire image volume results in high calculation times, a two-step approach starting with rough marker detection and then refining the localization through HT was adopted. The present paper starts by describing the algorithmic details and then presents a validation study on clinical image data.

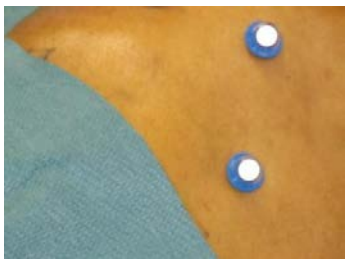


Fig. 1: Atesos single markers on patient body

Fig. 2: Single marker in CT image

2 Methods

Since HT is computationally expensive, it is not expected to be efficient when being applied to whole patient CT images. Thus, a two-part approach was chosen for the automatic SM localization: First, the whole patient CT image is processed in order to find volumes of interest (VOI). This step involves analysis of a big amount of data in a short time and therefore has to be expected to deliver low accuracy or even to detect VOIs which do not contain any SMs. Then, one of the two aforementioned methods can be applied to the VOI to determine whether a VOI actually contains a SM and if so, to precisely determine the center of the SM sphere.

VOI Detection: A morphological approach was implemented to scan the whole patient CT image for VOIs. By first applying a threshold based region growing algorithm (threshold: -500 HU), the patient body and the SMs are segmented. Afterwards, morphological opening with a spherical structuring element with 11 mm radius is applied to remove small structures such as single markers from the body surface. This operation is done slice-by-slice in order to increase performace which tends to be low when using large structuring elements. The resulting binary image is thereafter subtracted from the original binary image so that only SMs on the body surface and artifacts produced near the body surface and the CT table are kept. In order to distinguish the SMs from the artifacts, a size based relabeling is performed and only objects within a certain interval of physical volume ([750,2500] mm^3) are selected as VOIs. The VOI size is chosen such that each VOI can contain at most one SM (as the SMs are placed on the patient using a template, the minimal spacing between SMs is known).

Fig. 3: Binarized CT image

Fig. 4: CT image after opening

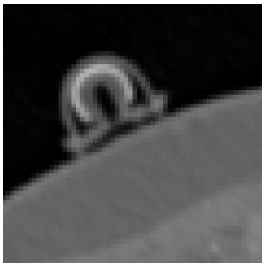


Fig. 5: CT image after subtraction

SM localization: When applied to a localization problem, the HT algorithm generates so-called accumulator image, each point of which has a value proportional to the probability that a sought-after shape with given geometric parameters (the SM sphere radius of 5 mm in the present problem) has its center in this point. Finding the centers of sought-after shapes is thus equivalent to finding the local maxima in the accumulator image. The HT algorithm can detect the absence of a SM in a VOI if the maximum in the accumulator image is below a certain value (i.e. the probability that the point is the center of a sphere is too low even though it is a maximum).

In the present implementation HT is first applied to each VOI as extracted from the original CT image. Afterwards, the six VOI for which the HT algorithm computed the highest maximum accumulator values are kept. For the remaining VOIs the following two steps are perforemed iteratively: First, the standard deviation of the maximum accumulator values is computed. Second, the VOI with the lowest maximum accumulator value is removed, if the standard deviation is above a certain threshold. This is done because the actual number of markers present in the image is not known (some might be outside the visible region). After this process, the size of the remaining VOIs is reduced to only contain the SM

sphere with a small margin. This new VOIs are oversampled to higher, isotropic resolution (as recommended in [5], Fig. 6) before applying HT again, such that the resulting accumulator image (Fig. 7) with higher resolution allows determining the SM center with higher accuracy.

The transparent SM shell is close to the SM sphere near its top and has a similar radius as the SM sphere. Moreover, the SM is not a complete sphere. Therefore maximum value of the accumulator image is biased towards the top of the SM shell. To correct this constant bias, the direction of the marker axis is determined by computing the intensity gradient at the center position calculated by the HT algorithm. The center position is then shifted along the marker axis towards the bottom of the SM by 0.75 mm (this value corresponds to the statistically appearing systematic error).

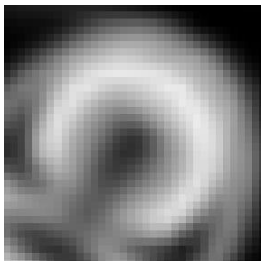


Fig. 6: VOI oversampled and reduced in size

Fig. 7: Accumulator image corresponding to Fig. 3

Implementation: The algorithm described above was implemented in C++ using the libraries provided with the Insight Toolkit [2]. Mosaliganti et al. have described and implemented an n-dimensional version of the HT algorithm for detection of spherical objects using the Insight Toolkit in work [3].

Validation: For performance assessment of the of the SM detection algorithm in terms of accuracy and speed, a set of five clinical CT scans was selected. The CT scans are each acquired on the patient's abdomen with six SM attached to the body. The in-plane resolution of the images varies from 0.72 to 0.87 mm and the z-spacing from 1.0 to 1.5 mm. For ground truth data acquisition, the center of each SM sphere was manually selected by an expert using a three view CT image viewer. The actual ground truth SM centers were determined by taking the mean of the three acquisitions for each SM (norm standard deviation all selected markers: 0.08 mm). Moreover, a benchmark framework for batch-processing the datasets with different methods and parameters to statistically evaluate the accuracy and speed of each method was implemented.

To be able to compare the automatic algorithm with the manual method, six users were asked to manually select the SM marker centers on the CAS-One IR using the standard interface (transversal view CT viewer). The SM center and time needed by the user to select the SM was measured for each SM. The resulting data was compared to the ground truth data.

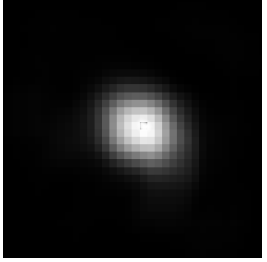
3 Results

Table 1 shows the SM center localization error from ground truth data (3D error) and time mean and standard deviation values for the six users. The average SM center localization error produced by the users was 1.1 mm and they needed an average time of 158.5 seconds to localize all six markers of each dataset.

Dataset number	3D error mean [mm]	3D error std.-dev. [mm]	Time mean [s]	Time std.-dev. [s]
1	1.2	0.5	167.8	45.3
2	1.1	0.8	176.1	45.1
3	1.2	0.6	156.8	41.1
4	0.8	0.5	129.4	27.6
5	1.1	0.5	162.3	33.2
All datasets	1.1	0.6	158.5	42.2

Table 1: 3D error and time requirements for manual SM detection by six different users

Table 2 shows the 3D error and time mean and standard deviation values for the automatic SM detection algorithm. This complete algorithm includes the morphological approach for VOI localization combined with the HT algorithm for SM



center computation. The algorithm was run 10 times to process each dataset. The average 3D error for automatic localization was 0.3 mm and the average time needed by the automatic method was 26.7 s.

Dataset number	3D error mean [mm]	3D error std.-dev. [mm]	Time mean [s]	Time std.-dev. [s]
1	0.3	0.1	18.3	0.0
2	0.3	0.1	22.1	0.0
3	0.3	0.1	30.7	0.0
4	0.4	0.1	30.2	0.0
5	0.4	0.2	32.0	0.0
All datasets	0.3	0.1	26.7	5.4

Table 2: Automatic SM detection algorithm 3D error and time mean and standard deviation values

4 Discussion

The automatic marker localization algorithm is roughly five times faster and three times more precise than the users. Moreover, the algorithm yields high reliability. For a total of 30 markers present in five different image series in different positions and orientations, all of the markers were correctly detected. However, further investigations are required to validate those findings.

One of the major disadvantages of the HT algorithm compared to other methods like template based image registration is the quantization of the output by the accumulator voxel resolution. Niblack and Petkovic show in work [4] a method involving smoothing and interpolation of the accumulator image to achieve sub-pixel precision when applying the HT algorithm. The implementation of a similar approach is subject of ongoing research.

The main shortcoming of the performance assessment is the low number of test datasets (five). We plan to add more datasets to the benchmark in the near future. Furthermore, an experiment involving a phantom with known geometry and marker centers should be performed in order to measure the precision of the manual and automatic localization more precisely.

In conclusion, we can state that automatic SM center localization is more accurate and faster than manual SM center localization and that it can be used to improve the over-all system precision and should therefore be integrated with the system as a standard feature.

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