Fuzzy Object Model-based Image Segmentation for *in vivo* Evaluation of Support Implant of Artificial Hip Joint

Chika Maeda, Syoji Kobashi, Katsuya Kondo, and Yutaka Hata
Graduate School of Engineering, University of Hyogo
2167, Shosha, Himeji, Hyogo, 671-2201, JAPAN
e-mail: maeda@comp.eng.himeji-tech.ac.jp

Nao Shibanuma
Kobe Kaisei Hospital
11-13-15, Shinohara-kitamachi, Nada-ku, Kobe, Hyogo, 657-0068, JAPAN

Masahiro Kurosaka
Graduate School of Medicine, Kobe University
7-5-1, Kusunoki-cho, Chuou-ku, Kobe, Hyogo, 651-0017, JAPAN

***Abstract*— Support implant has been used to reconstruct an artificial hip joint on the acetabulum in total hip arthroplasty (THA). After THA, we should diagnose periodically state of the support implant because the implants may be distorted or broken. This paper proposes an *in vivo* evaluation method using multidetector-row computed tomography (MDCT) images. The proposed method estimates the distortion degree of the support implant by comparing the 3-D geometric model of the support implant with the support implant region segmented from the MDCT images. The support implant region is segmented from the MDCT images using a fuzzy object model which can express knowledge about the shape of objects. The distortion degree is estimated based on a multiscale matching algorithm. The performance of estimating the distortion degree was validated through computer simulation experiments, phantom experiments *in vitro*, and subject experiments.**

I. Introduction

Total hip arthroplasty (THA) is an operation to replace the hip joint with an artificial hip joint [1]. In this operation, a support implant is used to reconstruct the artificial hip joint on the acetabulum. The artificial hip joints and support implants might be deformed or be broken by a strong load or with age. Because the deformed or broken implants can cause serious problems for patients, we should periodically diagnose the shape of the implants after THA.

There is a conventional method for diagnosing the support implant [2]. The method is that physicians visually evaluate the shape of the postoperative implant with X-ray images. However, it is impossible to obtain the 3-D shape of the implant because the X-ray image is a projection image. Also, quality of diagnosis depends on the physicians or X-ray images. Therefore, another method that quantitatively evaluates the implant based on 3-D form should be studied.

State of the arts of computed tomography (CT) has produced a new imaging modality; multidetector-row CT (MDCT) scanner. In comparison with conventional CT scanners, called singledetector-row CT (SDCT), the MDCT scanners can take 3-D images with high-contrast and high-spatial resolution by using multi detectors [3]. MDCT images have been applied to many studies, for example, to measure volumes of individual lobes [4] and to segment human airway [5]. However, MDCT images have not been used to diagnose the support implant because many artifacts are caused by the support implant made of titanium.

Our aim is to propose a computer-aided system to measure the distortion angle of the support implant and to detect lacks with MDCT images. Although the MDCT images have many artifacts caused by metal, we can classify the metal regions because there are differences of CT values between metal and the artifacts. Implants used by THA mainly consists of support implant, screw, cup, artificial condyle, and stem. The support implant and stem are made of titanium. Among metal implant, only the screw connects with the support implant and has same CT values to the support implant in MDCT images. To classify the support implant from the other implants, our method uses a fuzzy object model. The fuzzy object model assigns fuzzy degrees belonging to the support implant and the screws. By comparing the fuzzy degrees, we can segment the support implant. The distortion angle is estimated by using the multiscale matching algorithm. The proposed method was evaluated by three kinds of experiments that are computer simulation, phantom experiments and subjects experiments.

II. Materials

The structure of an artificial hip joint is illustrated in Fig. 1. Acetabular bone loss is filled with cancellous morselized bone, and is associated with cemented or noncemented acetabular components. The support implant is placed on the acetablum and is bolted by screws. The cup made of polyethylene is put on the support implant. The artificial condyle and the stem are embedded in the cup. In this study,

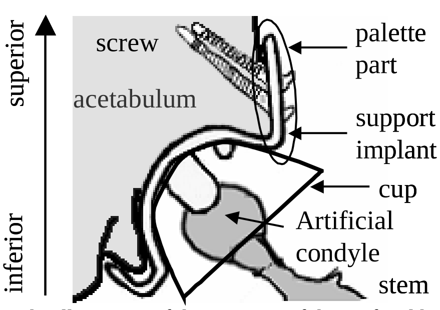


Fig.1. The illustration of the structure of the artificial hip joint.

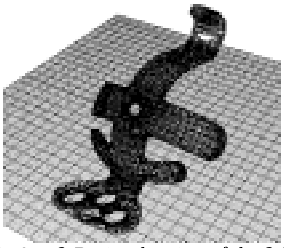


Fig.2. 3-D visualization of the 3-D geometric model of the support implant.

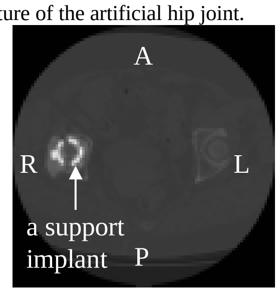


Fig.3. An example of MDCT image. (A; anterior, P; posterior, R; right, L; left)

we used KT plate (Kobe steel, Ltd, Kobe) as implants. The 3-D geometric model of the support implant was given by Stereolithograpy (STL) format whose mesh size was 0.01 mm. Fig. 2 shows the 3-D visualization of the 3-D geometric model.

We acquired MDCT images with two MDCT scanners (Aquilion; Toshiba, Tokyo, and Light Speed Ultra 16; GE Medical Systems, Milwaukee, WI). An example of MDCT image is shown in Fig. 3. As shown in this image, although there are artifacts caused by metal, there are differences of CT values between the implants and the artifacts. Also, we could not find any differences between an MDCT image taken by the one scanner and that taken by the other scanner.

III. Proposed Computer-Aided System with MDCT Images

Our system consists of three components. The first component extracts the support implant region from the MDCT images with a fuzzy object model. The second step is to find correspondence of characteristic points of 3-D geometric model and the support implant region extracted from MDCT images by using the multiscale matching algorithm [6]. At the third step, the distortion degree of the support implant is estimated using the found characteristic points and landmarks given by a user. The details of the each step are described in the following sections.

A. Extraction of the implant region and classification of the support implant using a fuzzy object model

In the MDCT images, CT value of metal is ranged from 3000 and 15000 Hounsfield unit (HU) and there are no human body soft/hard tissues that have similar CT values. So regions of the implants made of metal can be easily extracted by thresholding. Because the extracted implant region is composed of the support implant, screw, artificial condyle and stem, the next step is to classify the support implant from the other implants. Especially, the screw connects with the support implant, and it makes us difficult to classify the support implant. Although the shape of the implants is given by the 3-D geometric model, the relational locations vary subject by subject. That is, the screws are inserted through the holes of the support implant; however, the orientation and position in the holes are not strictly decided. To overcome this difficulty, we introduce a fuzzy object model. The fuzzy object model gives a fuzzy degree belonging to the implant based on the shape and the rough location. By comparing the fuzzy degrees, we can classify the voxel of interest into the support implant or the screw.

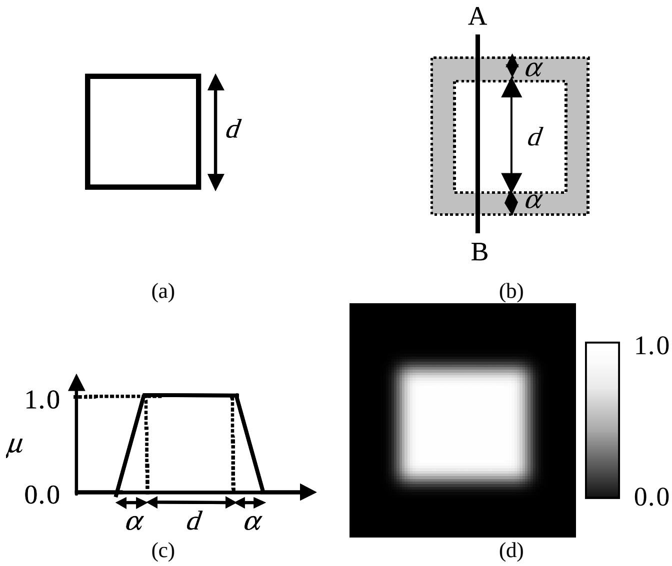


Fig.4. Fuzzy object model. (a) Geometric model. (b) Fuzzy object model. (c) Fuzzy membership function. (d) The fuzzy degree map.

The fuzzy object model is defined based on the 3-D geometric model of the object. For example, consider an object constructed by a geometric model illustrated in Fig. 4 (a). The object is fuzzified into the fuzzy object model shown in Fig. 4 (b) with a fuzzification parameter of α. The fuzzy object model includes the blurred region of the boundary. In the blurred region, we assign the higher fuzzy degree belonging to the object for the nearer points to the object and the lower degree for the farther points. The fuzzy degree profile on the line from A to B is shown in Fig. 4 (c). Using the fuzzy object model, a fuzzy degree belonging to the object is calculated as shown in Fig. 4 (d) for each voxel.

Our method classifies the implant region segmented by thresholding and labeling algorithms into the support implant

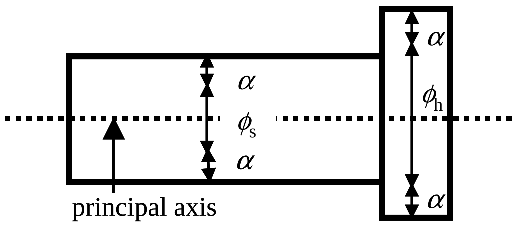


Fig.5. The fuzzy object model of a screw.

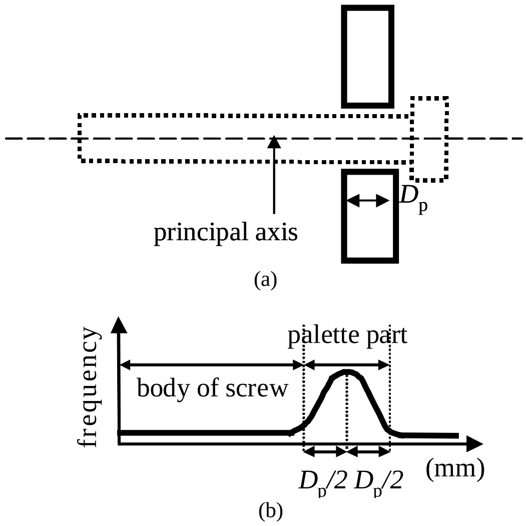


Fig.6. Fuzzy object model of the palette part: (a) The fuzzy object model. (b) Fuzzy membership function.

or the screws using fuzzy object models of the screw and the support implant. The fuzzy object model of the screw is defined as Fig. 5. In this model, ϕ_s and ϕ_h are diameters of the body and the head of the screw, respectively. To apply the fuzzy object model for the MDCT images, we first find the principal axis of the screw from the segment implant region. As shown in Fig. 1, top of the screw is orient to the superior of the body. So, we can segment parts of the screws by cutting the superior part of implant region with l mm (in our experiment, 30 mm was used). By calculating the principal axes of the segmented regions, we estimate the principal axes of the screws. Using the position of the superior top of the implant region and the principal axes, we can apply the fuzzy object model of the screw to the implant region.

The fuzzy object model of the palette part of the support implant is defined as Fig. 6 (a). In this model, D_p is the thickness of the palette part. To find the location of the palette part of the support implant from the segmented implant region, we calculate the frequency of voxels belonging to the implant region for each point on the principal axis along to the vertical direction of the principal axis. An example of frequency of voxels is given by Fig. 6 (b). In this figure, the small frequency means the body of the screw, and large frequency means the palette part of the

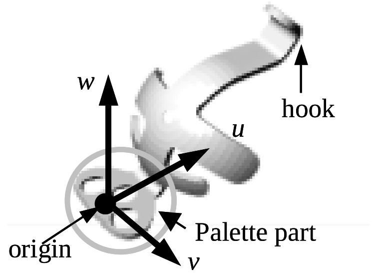


Fig. 7. Local coordinate system of the support implant.

support implant. So, we put the fuzzy object model of the palette part of the support implant at the highest frequency so that the fuzzy object model lies along the vertical direction of the principal axis.

Consequently, the fuzzy degree belonging to the screw, μ_s, and the fuzzy degree belonging to the support implant, μ_p, are assigned to all voxels of the implant region. We then segment voxels of the implant region that μ_p is higher than μ_s. And the other voxels are classified into the screw.

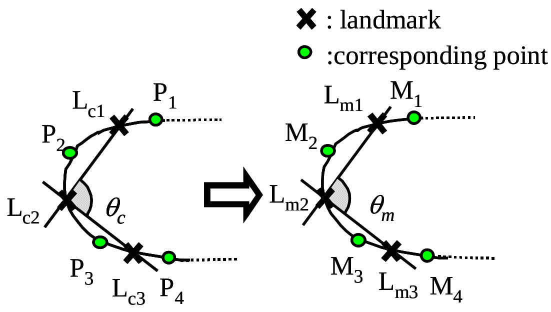
B. Multiscale matching on a 2-D projection

We define the local coordinate system (u,v,w) of the support implant as shown in Fig. 7. To apply this definition for the segmented support implant, we determine u-v plane by finding a plane parallelized to the palette part using the least-squares method (LSM). The coordinate origin is set at the center of gravity of the palette part. Also, the 3-D geometric model of the support implant is put according to the same coordinate system.

In out system, distortion angles are evaluated on a 2-D image that the 3-D image is projected on a plane that a user desired. The projection images are generated by means of maximum intensity projection (MIP) processing. For each projected image, we first extract outline of the segmented or the 3-D geometric model of support implant. We then apply the multiscale matching algorithm to find correspondences of the outline of the segmented support implant to that of the 3-D geometric model. The multiscale matching algorithm gives a set of characteristic points of the outlines.

C. Estimating of the distortion angle

Angles to be evaluated are defined by a user using landmarks set on the outline of the projection image of the 3-D geometric model. For example, when the user evaluates angle θ_c shown in Fig.8 (a), three landmarks, L_{c1}, L_{c2} and L_{c3}, are given by the user. Using the landmarks, θ_c can be defined as the angle between vector $\overrightarrow{L_{c2}L_{c1}}$ and vector $\overrightarrow{L_{c2}L_{c3}}$. To calculate the same angle on the segmented support implant, we should find landmarks corresponding to the user-given landmarks from the outline



(a) (b)

Fig. 8. Estimation of a distortion degree. (a) Outline of 3-D geometric model. Landmarks are manually set by a user. (b) Outline of the segmented support implant.

of the segmented support implant.

Let characteristic points of the 3-D geometric model be P_i ($1 \le i \le n$), characteristic points of the segmented support implant be M_i ($1 \le i \le n$), and P_i corresponds to M_i.

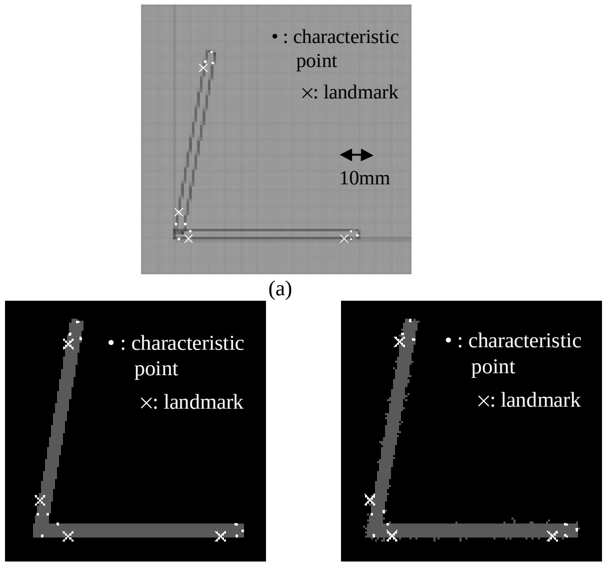
The characteristic point number is cyclic because the object is a closed-shape object. A landmark corresponding to a landmark L_{cj} on the 3-D geometric model is found by the following steps.

(1) Find the next characteristic points of the landmarks L_{cj} on the 3-D geometric model; P_i and P_{i+1}. For example, the next characteristic points of L_{c1} shown in Fig.8 (a) are P_1 and P_2.

(2) Calculate the run length of the outline from P_i to L_{cj}, and the run length from P_{i+1} to L_{cj}. Let the run length be *a* and *b*.

(3) On the outline of the segmented support implant, set a landmark, L_{mj}, at the point which internally divides the outline from M_i to M_{i+1} in the ratio of $a : b$.

In the same matter, the other landmarks on the outline of the segmented support implant are found. In the case of Fig.8 (a), by applying the above steps, L_{m1}, L_{m2} and L_{m3} on the outline of the segmented support implant are found for L_{c1}, L_{c2} and L_{c3} on the outline of the 3-D geometric model, respectively, as shown in Fig.8 (b). Using the found landmarks, we calculate an angle between vectors determined by the landmarks. Then, the distortion angle is calculated by differencing θ_c, which is an angle on the 3-D geometric model, and θ_m, which is an angle on the segmented support implant. For the reason of protecting the right of the 3-D geometric model, our system only shows the distortion angles but the measurement angles for users.



(a)

(b) (c)

Fig. 9. Examples of computer simulation data. (a) 3-D geometric model. (b) 80 degree with no noise. (c) 80 degree with 60 % noise.

TABLE I. DISTORTION ANGLES OF SUMILATION DATA.

Truth-value	0% noise [deg]		60% noise [deg]	
	Result	Error	Result	Error
90	90.00	0.00	90.12	0.12
85	84.87	-0.12	84.84	-0.16
80	79.93	-0.06	79.47	-0.53
45	44.99	-0.01	44.88	-0.12

IV. EXPERIMENTAL RESULTS

A. Computer simulation experiments

To evaluate the accuracy of measuring angles, we applied the proposed system to four angles of computer simulation data.

An example of the 3-D geometric model of computer simulation data is shown in Fig. 9 (a). The projection image that is shown in Fig. 9 (b) is same to 3-D geometric model. For this image, we set four landmarks shown in Fig. 9(a) to measure the angle between the lines. Also, to evaluate the performance for noise change, Gaussian noise with 60% was convoluted into the image as shown in Fig. 9 (c).

The angles measured by the proposed system are tabulated in Table I. As shown in this table, the proposed system could measure the angles with a mean absoluted error of 0.05 degree for the images with no noise. Also, for the images with 60% Gaussian noise, the proposed system could measure the angles with a mean absoluted error of 0.23 degree.

B. Experiments on MDCT images of phantoms

To evaluate the accuracy of measuring angles in the MDCT images, we made four phantoms made from titanium that is the same material of the support implant. The MDCT images used in this experiments were acquired with a matrix

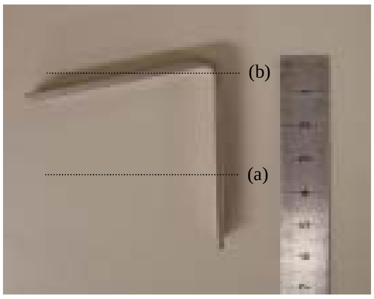
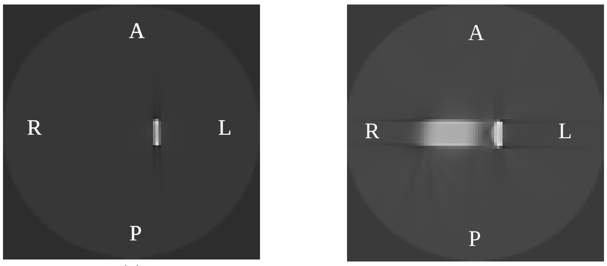


Fig. 10 Photography of the phantom.



(a) (b)

Fig. 11 Examples slice of the MDCT image of the phantom. (a) A slice of (a) in Fig. 10. (b) A slice of (b) in Fig. 10.

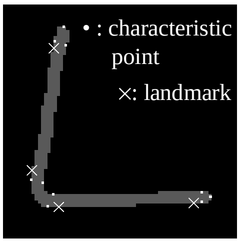


Fig. 12 A projection image of the MDCT image of the phantom. (a) A slice of (a) in Fig. 10. (b) A slice of (b) in Fig. 10.

TABLE II. DISTORTION ANGLES OF PHANTOM DATA.

Truth-value [deg]	Result [deg]	Error [deg]
90	90.95	0.95
85	84.00	-1.00
80	79.62	-0.38
45	44.09	-0.91

of 512×512, a pixel size of 0.234×0.234 mm, a slice thickness of 0.5 mm, a tube current of 300 mA and a tube voltage of 120 kV. The number of slices was 611. The 3-D geometric model and the landmarks to calculate the angle are same as those used in the computer simulation experiments. Photography of the phantom is shown in Fig. 10. Fig. 11(a) and (b) show a slice of the MDCT image of the phantom. A projection image of phantom is shown in Fig. 12. The results of measuring the angles by the proposed method are tabulated in Table II. This table shows that the system could measure the angles with a mean absoluted error of 0.81 degree.

C. Experiments on THA patients

We have applied the proposed system to MDCT images taken from 5 subjects (mean age [± SD] 66.3±7.9 years, and 5-56 months after THA). The MDCT images used in this study were acquired with a matrix of 512×512, a pixel size of 0.441×0.441 mm to 0.637×0.637 mm, a slice thickness of 0.5 mm, a tube current of 300 mA and a tube voltage of 120 kV. For each subject, over 460 slices were taken so that the whole implant was covered.

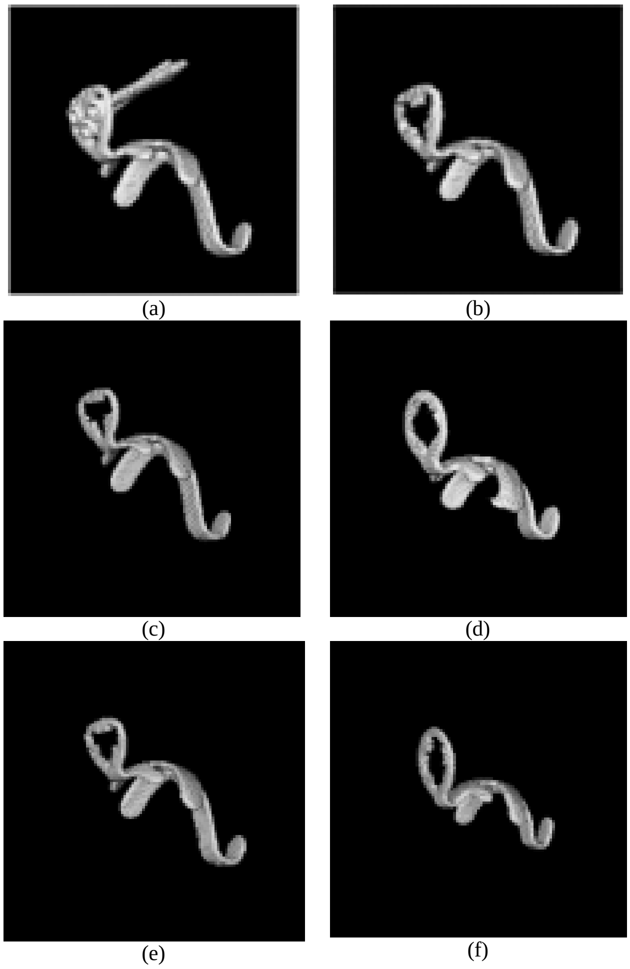


Fig. 13 Segmentation of the support implant by fuzzy object model. (a) Segmented implant region of A. (b) Segmented support implant region of A. (c) Segmented support implant region of B. (d) Segmented support implant region of C. (e) Segmented support implant region of D. (f) Segmented support implant region of E.

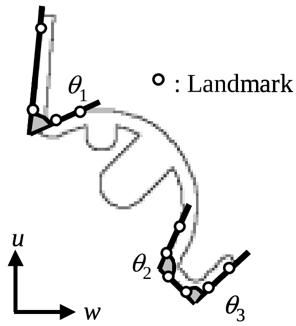


Fig.14. Definition of angles.

For subject A, the extracted implant region by thresholding and labeling is shown in Fig. 13 (a). The support implant region which was segmented by using the fuzzy object model of subject B, C, D, and E are shown in Fig. 13 (b), (c), (d), (e) and (f). As shown in the images, the

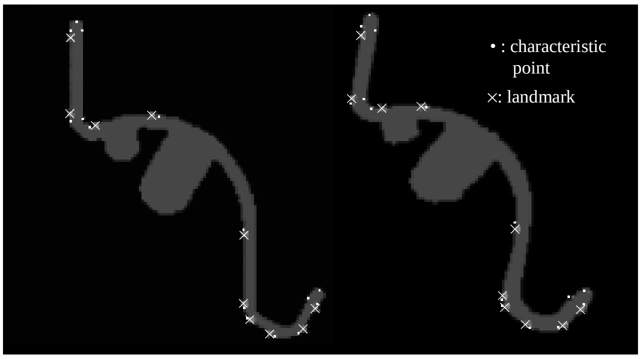


Fig.15. Matching result of A. left; projection image of the 3-D geometric model, right; projection image of the segmented support implant.

TABLE III. THE DISTORTION ANGLES OF SUBJECT'S DATA.

SUBJECT	$\Delta\theta_1$[deg]	$\Delta\theta_2$[deg]	$\Delta\theta_3$[deg]
A	2.71	9.32	-4.41
B	-0.83	1.72	16.31
C	3.01	2.54	5.28
D	3.95	4.85	-2.23
E	0.66	0.62	3.72

support implant region was well segmented.

To evaluate the distortion of the support implant embedded in the body of the subjects, three distortion angles were defined by a physician in *w-u* plane as shown in Fig. 14. Fig. 15 shows the 2-D projection images of the segmented support implant and the 3-D geometric model. By applying the multiscale matching algorithm to the images, we obtained characteristic points. The number of characteristic points was 27. In Fig. 15, some of the characteristic points obtained by the multiscale matching algorithm are shown by dots. The distortion angles measured by the proposed system are tabulated in Table III. In this table, $\Delta\theta_3$ of subject B was clearly larger than the other evaluating angles and the other subject B. In the case of Subject B, a screw embedded in the body of the subject was hardly distorted. This means the support implant of subject B would be charged by a strong load. The large distortion of $\Delta\theta_3$ of subject B supports our hypothesis.

V. CONCLUSION

In this paper, we have proposed the *in vivo* evaluation system of the support implant using MDCT images. Our proposed system can measure the distortion of evaluating angles *in vivo*. This system can strongly support the postoperative periodical prognosis.

To evaluate the performance of the proposed system, we have done three types of experiments; computer simulation, phantom experiments and subject experiments. The first and second experiments for simple objects showed that the method could measure the angles within the error of 1.0 degree although the images included 60% Gaussian noises. In the third experiment for five patients after THA, the proposed fuzzy object model segmented the support implant successfully. Also, we have measured the distortion angles of the segmented support implants. The results were correlated with the state of the screws. Therefore, we are considering that the proposed system can find the irregular of the support implant before the serious problems such as broken or damage occur. Because the support implants shown in our experiments have embedding the body of the subjects, we can not evaluate the accuracy of measuring the angles. So, we will evaluate the accuracy by applying the proposed method to support implants that are distorted artificially *in vitro*. Also, we will apply our method to find lack of the support implant, and will apply for another implants, for example, femoral component and tibia tray.

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