Locating Fetal Facial Surface, Oral Cavity and Airways by a 3D Ultrasound Calibration Using a Novel Cones’ Phantom

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SUMMARY Toward the actualization of an automatic navigation system for fetoscopic tracheal occlusion (FETO) surgery, this paper proposes a 3D ultrasound (US) calibration-based approach that can locate the fetal facial surface, oral cavity, and airways by a registration between a 3D fetal model and 3D US images. The proposed approach consists of an offline process and online process. The offline process first reconstructs the 3D fetal model with the anatomies of the oral cavity and airways. Then, a point-based 3D US calibration system based on real-time 3D US images, an electromagnetic (EM) tracking device, and a novel cones’ phantom, computes the matrix that transforms the 3D US image space into the world coordinate system. In the online process, by scanning the mother’s body with a 3D US probe, 3D US images containing the fetus are obtained. The fetal facial surface extracted from the 3D US images is registered to the 3D fetal model using an ICP-based (iterative closest point) algorithm and the calibration matrices, so that the fetal facial surface as well as the oral cavity and airways are located. The results indicate that the 3D US calibration system achieves an FRE (fiducial registration error) of 1.49 ± 0.44 mm and a TRE (target registration error) of 1.81 ± 0.56 mm by using 24 fiducial points from two US volumes. A mean TRE of 1.55 ± 0.46 mm is also achieved for measuring location accuracy of the 3D fetal facial surface extracted from 3D US images by 14 target markers, and mean location errors of 2.51 ± 0.47 mm and 3.04 ± 0.59 mm are achieved for indirectly measuring location accuracy of the pharynx and the entrance of the trachea, respectively, which satisfy the requirement of the FETO surgery.

key words: 3D location, fetal oral cavity and airways, 3D ultrasound calibration, iterative closest point algorithm, 3D fetal model, 3D electromagnetic tracking device

1. Introduction

1.1 Background and Purpose

Congenital diaphragmatic hernia (CDH) is a severe birth defect of the diaphragm, which has a prevalence of 1 in 2,000–3,000 newborns and leads to approximately 8% of the known major congenital anomalies. In recent clinical practice, it has been reported that severe CDH could be treated in utero by a minimally invasive surgery (MIS) called fetoscopic tracheal occlusion (FETO) [1], which places a detachable balloon into the fetal trachea to prevent pulmonary hypoplasia by increasing the pressure of the chest cavity. In order to perform an FETO surgery, a fiber endoscope having a diameter of 1.3 mm within a cannula (Karl Storz) having a diameter of 3.3 mm is inserted into the amniotic cavity through the abdominal and uterine walls, towards the fetal mouth and trachea, navigated by 2D ultrasound (US) images and fetoscopic images [2]. However, this operation is so difficult and risky that high-level surgical skills are necessary. To facilitate this surgery, a flexible wire-driven surgical tool, whose posture can be transformed to fit the internal structure between the fetal oral cavity and trachea, has recently been developed [3], but the operation of this surgical tool is still difficult without an automatic navigation system.

Meanwhile, real-time 3D US images as an intraoperative guide have been introduced to fetal MIS surgeries [4], [5], due to their cost efficiency, real-time imaging, lack of radiation exposure, and impact-free characteristic compared to preoperative MR or CT modalities. Unfortunately, 3D US images have many disadvantages. Due to the speckle noise, the imaging quality is very poor. The imaging field of view (FOV) is also quite limited. Frequently, some critical internal organs are difficult to visualize and identify from 3D US volumes because of their low resolution and the echogenicity relative to the target organs.

1.2 Related Work

1.2.1 Navigation Systems for the FETO Surgery

In conventional navigation systems for FETO surgery, real-time 2D or 3D US images are applied simply to visualize the position of the surgical tool and fetal mouth, without any further processing of US images or an accurate location of the target organs [1], [4], [5]. Moreover, since the surgical tool and fetal mouth are still difficult to clearly distinguish using 2D or 3D US images because of speckle noise, shadows, and a low signal-to-noise ratio, surgeons are required to have a wealth of experience in using US images. The group of Deprest examined US images to determine the fetal and placental position for optimal trocar insertion, and guide a cannula with a purpose-designed trocar to insert into the amniotic cavity to the fetal mouth. In succession, the fetoscope was introduced into the fetal mouth as a guide and advanced over the tongue to the pharynx, then to the larynx with the epiglottis, and finally through the vocal cord to the trachea [1]. Ruano et al. reported a guidance of 4DUS to direct a cannula with the fetoscope into the fetal oral cavity, which allowed imaging of the entire fetal face and the insertion of the cannula toward the fetal oral cavity [4]. Tchirkov [5] also discussed real-time 3D US guidance in FETO surgery to reduce the surgical risk. None of these works achieved automatic and accurate location of the fetal...
facial surface, oral cavity, and airways in 3D US images.

1.2.2 Overview of 3D Ultrasound Calibration Methods

In recent decades, much research has been undertaken to make US calibration more reliable, accurate, and simultaneously easier and quicker to perform. With the commercial availability of a new generation of 3D US machines, real-time 3D US calibration based on real-time 3D US volumes offers many new opportunities for computer-assisted diagnosis, therapy, and intervention. Usually, calibration methods are classified with respect to the target geometry (a phantom) they rely on. 3D US calibration methods using a 3D US probe have been reviewed specifically in [6],[7].

The simplest phantoms are probably single-point and multi-point targets. This can be formed by a pair of cross-wires or a stylus [7]. Poon and Rohling [7] compared three phantoms, namely an IXI-fiducial wire phantom, a cube phantom, and a stylus based on a 3D curved-array US probe. They obtained the root mean square (RMS) errors of the point accuracy measure of 2.15 mm (IXI-wire), 4.91 mm (cube), and 2.36 mm (stylus) through an optical tracking system. Lang et al. [8] examined two similar solutions based on 2D US images [9],[10] extended to 3D using EM tracking, and obtained an average distance error of 1.39±0.54 mm. Nevertheless, most of them share the alignment and feature extraction problems.

Z-fiducial (N-fiducial) phantom addresses the alignment problem of point target methods. Bouchet et al. [11] designed a Z-phantom consisting of 39 nylon wires based on swept-volume US and an optical tracker. The maximum errors in the three dimensions of the volume are 0.4 mm in the elevation direction, 1.5 mm in the lateral direction, and 1.1 mm in the axial direction, leading to a total target location error of 1.9 mm. However, this technique required an average of 300 points for 3D US volumes, which made the calibration system inefficient.

Plane phantom methods are based on detection of the intersecting line of a planar surface with the 2D US beam. Michael et al. [12] optically tracked a single plane membrane phantom, and achieved an RMS distance error of 1.15 mm. But the major drawback of single-plane phantoms resides in their barely discriminative geometry. Meanwhile, the 12-step acquisition protocol is necessary for obtaining robust results, which leads to a lot of redundancy. Another drawback is that the overall calibration time is about 20 minutes, and the feature extraction problem results in a visual verification and eventually a correction.

Registration-based methods rely on surface or intensity based registration techniques and therefore can be performed on images of objects with arbitrary shape. Lange and Eulenstein [13] compared two image registration-based methods based on swept-volume 3D US, i.e., the tracked phantom (TP) approach and hand-eye (HE) calibration. The TP approach registered a US volume of a phantom with its associated CT volume, and the HE calibration registered two US volumes acquired from two different direc-

1.3 Proposed Approach

In an FETO surgery, the surgical tool with a fetoscope is inserted through the abdominal wall into the uterus, and a detachable balloon is placed above the fetal trachea for the tracheal occlusion, as shown in Fig. 1, to stimulate lung growth by increasing pressure in the fetal chest cavity.

For the FETO surgery, the location of the surgical tool, the fetus and the critical internal organs plays an important role on reducing the surgical risk. On one hand, 3D US images can allow only 3D modeling of the surface of a fetus,
but cannot 3D-model internal organs of a fetus, because the internal organs cannot be distinguished in 3D US images. Although MR images are available to 3D-model internal organs of a fetus in actual clinical applications, in case of our research, it is very difficult to get a permission to use real fetal MR images due to privacy problems in Japan. Therefore, as an alternative for MR images, we use models of fetal phantoms with internal structure. The model is registered to the 3D US images so that the internal organs are located in the 3D US images.

To do this, we use resin fetal phantoms without internal structure instead of real fetus in the mother’s body, where normally resin phantoms with internal structure are also not available. Since the resin phantom does not have the internal structure, after we laser-scan the phantom, we designed the internal structure in the phantom’s model, which was 3D reconstructed from the laser-scanned data. Accordingly, we propose a surgical navigation scheme based on fetal phantoms, the designed internal structure, real-time 3D US images, and a novel 3D US calibration system.

Figure 2 shows a block diagram of the proposed approach, which consists of an offline and online process. The offline process prior to surgery includes reconstruction of 3D fetal model with oral cavity and airways, and estimation of the transformation matrix of the 3D US calibration system by the novel cones’ phantom and EM tracking device. Note that this paper uses resin fetal phantoms for the offline and online processes because of difficulties in using real fetuses for the experiments. The online process starts with obtaining 3D fetal US images by scanning a fetal phantom in a water tank with a 3D US probe. Then, a 3D fetal facial surface is extracted from the 3D US images and registered with the 3D fetal model. After the registration, the 3D fetal model located in the 3D US space is transformed into the 3D tracking space by the estimated transformation matrix, where the 3D US space denotes the coordinate system of 3D US images, and the 3D tracking space denotes the world coordinate system of the 3D EM transmitter. Finally, the 3D fetal facial surface, oral cavity, and airways are accurately located in the 3D tracking space.

1.4 Organization

The rest of the paper is organized as follows: Section 2 introduces the reconstruction of the 3D fetal model with the oral cavity and airways. Section 3 describes a 3D rigid registration between the 3D fetal model and 3D US images. Section 4 proposes a real-time 3D US calibration system based on a novel cones’ phantom. Section 5 presents validation methods and experimental results. Finally, Sect. 6 gives a conclusion and offers ideas for future work.

2. 3D Fetal Model

2.1 3D Fetal Facial Surface

Since the internal anatomies of the oral cavity and airways are difficult to visualize and distinguish from 3D US volumes due to their low resolution, we design a 3D fetal model with such anatomies. At first, the surface of the 3D fetal model is created by scanning a physical fetal phantom with an untouched high-speed 3D scanner-3030RGB/MS. First, the phantom is made to stand in the front of the scanner. Next, the phantom on the rotating platform rotates along a complete circle, and each turn is set to 10°. Finally, the 3D fetal facial surface can be reconstructed as 3D point cloud data obtained by the untouched 3D scanner, as shown in Fig. 3 (a).

2.2 Design of the Fetal Oral Cavity and Airways

The designed internal anatomies include the structures of the oral cavity, pharynx, larynx, trachea, and esophagus. As the FETO surgery is often performed at about 26–29 weeks gestational age (GA) [2], we select the average size for each part at about 24–32 weeks GA. These structures [21] are drawn by a 3D CAD design software (Solidworks 2008). To simplify the design, the cross-sectional shapes of all tracts are considered as ellipses or circles. The size of each part is determined by referring to [22]–[24]. Through the manual rotation and translation of the designed structure in 3D space, we can achieve a 3D fetal model with an oral cavity and airways, as shown in Fig. 3 (c).
sound speeds in, densities of, and acoustic impedances (fluid and water are also listed according to [25]. Note that ble 1, in which sound speeds in and densities of amniotic fetus, we measured sound speeds in and densities of water experimental environment and the environment of the real ff
to compare di[...](Fig. 4 (a)). The V6-2 3D water tank with the Philips iU22 US system and a V6-2 3D In the online process, we scan a physical fetal phantom in a phantoms at room temperature as indicated in Ta- 3. 3D Rigid Registration
3.1 3D Fetal Ultrasound Images

In the online process, we scan a physical fetal phantom in a water tank with the Philips iU22 US system and a V6-2 3D US probe to obtain 3D US images (Fig. 4 (a)). The V6-2 3D US probe has a 6 to 2 MHz extended operating frequency range and a field of view of 66°. All acquired volumes have a size of 512 (x) × 510 (y) × 256 (z) voxels with the scaling factors $s_x = 0.35 \text{ mm/voxel}$, $s_y = 0.23 \text{ mm/voxel}$, $s_z = 0.43 \text{ mm/voxel}$, where the $x − y − z$ coordinate system of the 3D US image, which is decided by the position and orientation of the 3D US probe, is defined in Fig. 4 (a).

Our phantom based experimental environment can simulate the environment of the real fetus in the uterus (amniotic fluid) accurately as explained in the following. In order to compare difference of ultrasound imaging between the experimental environment and the environment of the real fetus, we measured sound speeds in and densities of water and our phantoms at room temperature as indicated in Table 1, in which sound speeds in and densities of amniotic fluid and water are also listed according to [25]. Note that sound speeds in, densities of, and acoustic impedances ($Z_{ai}$) of water and amniotic fluid are similar to each other, where acoustic impedance $Z_{ai}$ is calculated by

$$Z_{ai} = \rho D \quad (1)$$

In Eq. (1), $\rho$ and $D$ denote the density and sound speed, respectively. Table 1 shows that the difference between the sound speeds measured by us and shown in [25] in water at room temperature is approximately 0.9%, which is very small. Thus, we can infer that the error between the measured sound speed in our fetal phantoms and their ground truth should be acceptably small. Using Eq. (1), the acoustic impedance of our phantoms is calculated as shown in Table 1.

For ultrasound imaging, ultrasonic waves are emitted from a transducer, and partly reflected back to the transducer as echoes from boundaries between two adjacent objects. The amount of the reflected echoes depends on the difference in acoustic impedances between the two objects such as tissues traversed by the beam, where this difference in $Z_{ai}$ is commonly referred to as impedance mismatch. The larger the impedance mismatch is, the larger the amount of reflection is, and the smaller the amount of transmission is. The reflection coefficient $R_{US}$ is defined as a ratio of the intensity of the reflected wave relative to that of the incident wave as follows [27],

$$R_{US} = \frac{(Z_{ai2} - Z_{ai1})^2}{(Z_{ai2} + Z_{ai1})^2} \quad (2)$$

where $Z_{ai1}$ and $Z_{ai2}$ are the acoustic impedances of the two objects that form the boundary. Table 2 shows the values of $R_{US}$ (%) at various boundaries. At boundary between amniotic fluid and human skin, only 0.2% of the incident energy is reflected, and 99.8% of the energy is transmitted across the boundary. Although this reflected energy is much smaller than 31.8%, the reflection coefficient at boundary

| Table 1  | Sound speeds, densities and acoustic impedances of different materials. |
|----------|----------------------------------------------------------------------|
| Materials | Sound speed ($D$) ($\text{m s}^{-1}$) | Density ($\rho$) ($\text{kg m}^{-3}$) | Acoustic impedance ($Z_{ai}$) ($\text{10}^6 \text{ kg m}^{2} \text{ sec}^{-1}$) |
| amniotic fluid (ref. [25]) | 1510 | 1.01 | 1.33 |
| water (ref. [25]) | 1500 | 1 | 1.50 |
| water (measured) | 1486 | 1 | 1.49 |
| fetal phantoms (measured) | 1208 | 0.96 | 1.16 |
| human skin (ref. [26]) | | | 1.68 |
| human muscle (ref. [27]) | | | 1.70 |
| human skull (ref. [27]) | | | 6.10 |

| Table 2 | The values of $R_{US}$ (%) at various boundaries. |
|----------|----------------------------------------------------------------------|
| Boundary | The reflection coefficient ($R_{US}$) |
| amniotic fluid - human skin | 0.2% |
| human skin - human muscle | 0.004% |
| human muscle - human skull | 31.8% |
| water (measured) - fetal phantoms | 1.6% |
between human muscle and human skull, it is sufficient to reveal the borders of fetal faces according to [28], in which clear clinical 3D US data of fetal faces are presented. Therefore, the faces of our fetal phantoms in a water tank can be imaged reasonably due to the reflection coefficient value 1.6% at boundary between water and the phantoms. Then, the gray-levels of the phantoms’ faces should be between the gray-levels for real fetal faces and real fetal skulls in 3D US images, while gray-levels for the phantoms and real fetal faces could be close to each other. Actually, by visually comparing US images for our phantoms with real fetal faces [28] and skulls [29], it turns out that gray-levels for our phantoms and real fetal faces are almost identical, while real fetal skulls are brighter due to the larger reflection coefficient value (31.8%).

3.2 3D Fetal Facial Surface Extraction

Unlike MR or CT imaging technology, 3D US images do not have high resolution, and the imaging quality of US is easily affected by phantom material and air bubbles in the water. Therefore, we propose a method to extract the 3D fetal facial surface by scanning the slices in an \( x - y \) plane. Herein, we use a fetal phantom at the gestational age of 30 weeks as an example, and its 3D US data (Fig. 4 (b)) that has been pre-processed by Gaussian filter and threshold segmentation are shown in Fig. 4 (c), where 3D US probe is placed above the fetal head, and the fetal head can be centered in the 3D US space \((x - y - z)\) coordinate system), because the fetus is assumed to be fixed in uterus during the operation. The procedure for this method is described in the following steps, where the slice of \( z = 128 \) is an example in Fig. 4 (d).

**Step-1:** The boundaries in the 2D slice of \( z = 128 \) are detected by canny edge detection (Fig. 4 (e)).

**Step-2:** The fetal face is detected by fitting an ellipse to the detected boundaries (Fig. 4 (e)) via an improved iterative randomized Hough transform (IRHT) algorithm proposed in [30], so that five elliptical standard parameters \( [x_0, y_0, a, b, \phi]\) \((a > b)\) are estimated. Next, a square region of interest (ROI) centered at \((x_0, y_0)\) with the length of \( a \times 1.1 \times 2 \) is calculated.

**Step-3:** The largest connected region is selected in the ROI area, and filtered by binary morphologic operations and a hole-filling filter, as shown in Fig. 4 (f);

**Step-4:** The contour of the thresholded region is detected by a binary contour filter, and the mid-curves of the contour are detected by vertical raster scan, as shown in Fig. 4 (g). Next, the edges on the contour above the mid-curves are remained (Fig. 4 (h)), and the largest connected curve is detected as the upper edge (Fig. 4 (i)).

**Step-5:** Repeat the steps from (3) to (4) in the slices from \( z = 50 \) to \( z = 200 \), and then a 3D point cloud of the fetal facial surface is extracted, as shown in Fig. 4 (j).

On the other hand, it is straightforward to extract the corresponding facial surface from the 3D fetal model simply by setting the range on the \( x, y \), and \( z \) axes (Fig. 4 (k)).

3.3 Registration Based on Iterative Closest Point Method

The iterative closest point (ICP) method for the registration of 3D point clouds was proposed by Yang et al. [31] and Besl et al. [32]; It has been widely used in a variety of fields including medical images, because of its good accuracy and fast speed. Given two point clouds \( A = a_i \) \((i = 1, 2, \ldots, N_A)\) and \( B = b_j \) \((j = 1, 2, \ldots, N_B)\), the transformation between data \( A \) and data \( B \) is assumed to be linear with respect to a rotation matrix \( R \) and translation vector \( t \). The goal of the ICP algorithm is to find the transformation parameters for minimizing the error (mostly least squares) between the transformed data \( B \) and the closest points of the data \( A \), which is described by Eq. (3) [33], where \( a_{r(i)} \) is the point of the data \( A \) paired with \( b_j \).

\[
(R, t) = \arg \min_{R, t} \sum_{i=1}^{N_A} |a_{r(i)} - (Rb_j + t)|^2
\]  
(3)

3.3.1 Coarse Registration

For the purpose of improving the efficiency, accuracy, and robustness of the conventional ICP algorithm, this paper proposes an ICP-based registration algorithm, which consists of coarse registration and fine registration. In the coarse registration, facial feature points, i.e., nose tip, two eyes’ inner corners, and nose’s upper bridge, are detected in the two extracted 3D fetal facial surfaces from 3D US images and the 3D fetal model. As introduced in [34], the shapes of the nose tip, two eyes’ inner corners, and nose’s upper bridge are respectively elliptical convex, elliptical concave, and hyperbolic convex, which can be described by the mean (H) and Gaussian (K) curvatures. From [35], a surface that has either a peak or a pit shape has a positive Gaussian curvature value \( (K > 0) \). The nose tip has a peak surface type, and each of the two eyes’ inner corners has a pit surface type that is detectable based on the Gaussian curvature. These points should have the highest positive Gaussian curvature values among the points on the facial surface. However, since the unpredictable sharp spike noise on the 3D facial surfaces may result in a false feature detection, a boosting traversal scheme based on the spatial relations among key features proposed in [36] is applied to guarantee a successful detection of the key facial features.

About the feature detection, we use the extracted 3D point cloud (Fig. 4 (j)) from 3D US images as an example for explaining the procedure. The steps are as follows:

1. The depth image of the facial surface is mapped to 2D space, as shown in Fig. 5 (a).
2. The depth map is smoothed (Fig. 5 (b)) by a median filter (by a \( 5 \times 5 \) window) and a Gaussian filter (by a \( 5 \times 5 \) window, and the Gaussian sigma, which is the standard deviation of the Gaussian distribution, is set as 1.25) to remove sharp spikes and noise. Then the depth map is thresholded to detect regions of high curvatures, and to reject points with low curvatures by \(|H| \geq T_h\) and \(|K| \geq T_k\), where \( T_h = 0.02 \)
and $T_k = 0.00025$ are predefined by experiments.
(3) The candidate regions of the nose ($H > 0 \& K > 0$) and two eyes’ inner corners ($H < 0 \& K > 0$) are selected from the thresholded depth map (Fig. 5(c)), and are sorted in descending order by the standard deviation of Gaussian curvatures of each region, respectively.
(4) The three regions are selected in sequence from the sorted candidate regions of the nose and eyes’ inner corner (e.g., three black areas in Fig. 5(c)).
(5) The positions of the points with maximum Gaussian curvature in the selected three regions are labeled as feature points (Fig. 5(d))[37], where the two blue points indicate the positions of the two eyes’ inner corners, and the green point indicates the position of the nose tip.
(6) The candidate regions for the nose’s upper bridge are classified by HK classification ($H > 0, K < 0$) and the threshold of the depth map ($|H| \geq 0.005, |K| \geq 0.00005$), e.g., the gray regions in Fig. 5(d).
(7) The candidate region closest to the midpoint of the two eyes’ inner corners is selected as the region of the nose’s upper bridge, whose centroid is detected as the position of the nose’s upper bridge, e.g., the black point in Fig. 5(d).
(8) The spatial relationship among these four features is examined by the filter proposed in [36]. If the filter is satisfied, these feature points are finally determined; otherwise, return (4) to traverse all candidate regions until the filter is satisfied.

The boosting traversal scheme based on the spatial relations among key features [36] ensures that the four feature points can be detected successfully, as shown in Fig. 5(e). Similarly, the corresponding feature points of the 3D fetal model (i.e., the red points in Fig. 5(f)) are detected and registered with the four feature points detected from 3D US images (i.e., the blue points in Fig. 5(f)) by the ICP algorithm, where the 3D gray point cloud in Fig. 5(f) shows the 3D facial surface extracted from the 3D US images.

3.3.2 Fine Registration

After the feature point-based coarse registration described in Sect. 3.3.1, fine registration for the two point clouds is performed for better efficiency, accuracy, and robustness. Then the ICP-transformation matrix in the left side of Eq. (3) is calculated by the ICP algorithm. The result is shown in Fig. 6(a), where the right red source point cloud (containing 5049 points) is extracted from the 3D fetal model, the left blue target point cloud (containing 17863 points) is extracted from the 3D US images, and the left green resulting point cloud is transformed from the right red source point cloud by the ICP-transformation matrix.

Based on the ICP-transformation matrix, we can transform all the points of the 3D fetal model with the oral cavity and airways into 3D US space. The results in Fig. 6(b) and (c) illustrate that the transformed 3D fetal model coincides very well with the fetal facial surface in the 3D US images.

4. 3D Ultrasound Calibration

3D US calibration aims to determine the spatial transformation for mapping points from the 3D US space to the 3D tracking space. The transformation comprises six parameters-3 translations in the direction of the $x$, $y$, and $z$ axes and the 3 rotations, azimuth, elevation, and roll, about these axes.

4.1 Cones’ Phantom

Figure 7 shows the proposed calibration setup, in which 12 plastic cones, whose tips are utilized for the calibration, are placed on the bottom of a water tank. The 3D US probe with a 3D tracking sensor is fixed above the phantom by a plastic holder, so that the beam surface contacts the water. The transmitter of the 3D EM device is settled near the water tank. The $x - y - z$ system is the coordinate system of 3D US images (see also Fig. 4(a)), the $x' - y' - z'$ system is the coordinate system fixed to the 3D US probe, and the $x'' - y'' - z''$ system is the world coordinate system of the 3D EM transmitter.

The phantom is composed of 12 transparent resin cones of six different types. The bottom diameters of all types are 30 mm, and the heights of the six types are 30 mm (C-I), 40 mm (C-II), 50 mm (C-III), 60 mm (C-IV), 70 mm (C-V), and 80 mm (C-VI), respectively. Since the field of view of 3D US images is fan-shaped, its top is narrow and its bottom is wide, as shown in Fig. 4(c) and Fig. 4(d). Accordingly, in the phantom, as shown in Fig. 8(a), the two tallest cones are arranged in the middle, and other lower cones are arranged on both sides, i.e., the cones of No.5 and No.6 are C-V, No.7
and No.8 are C-VI, No.1 and No.2 are C-I, No.3 and No.4 are C-II, No.9 and No.10 are C-III, and No.11 and No.12 are C-IV. In addition, as shown in Fig. 8 (b), nine cones are arranged as a target model used for the validation in Sect. 5.1, where the cones from No.4 to No.6 are C-IV (the taller ones in the middle), and the others are C-I (the lower ones on both sides).

4.2 Calibration Matrix

The proposed 3D US calibration system addresses the feature extraction problem, i.e., the fiducial points (the tips of the cones are shown as white points in Fig. 9 (a)) are identified automatically and precisely in 3D US images by the following steps.

1) The 2D slice of \( y = 130 \) (about the quarter position in the \( y \) direction) is extracted from 3D US images. It includes the 12 ellipses that correspond to the 12 cones in the phantom (Fig. 9 (b)). Note that in the 2D slice the cross section of each cone is observed as an ellipse due to US deformation.

2) Through the bilateral filter, K-mean segmentation, and distance transformation in the 2D slice, the skeletons of the 12 ellipses are extracted (Fig. 9 (d)).

3) The 12 ellipses are detected by the improved IRHT method [30] with the restrictions of \( a \leq 43, b \leq 43, \) and \( e \leq 0.7 \), where the semi-major axis \( a \) and semi-minor axis \( b \) of each cone should be less than \( 256/6 = 43 \) (256 is the maximum value of the \( z \)-axis), because a total of three cones are arranged in \( z \) direction, and \( e \) denotes the eccentricity of the detected ellipse. Since the US deformation is limited, the ellipses deformed from the circles of the cross sections of the cones should not be so flat that the eccentricity of the ellipses could be confined in the range of \( e \leq 0.7 \). Multiple-ellipse detection is accomplished by the method in [38], and then five elliptical standard parameters \([x_0, z_0, a, b, \phi] (a > b)\) of each ellipse are estimated.

4) Similarly, from the five 2D slices in \( y \) direction (i.e., \( y = 130, 135, 140, 145, \) and 150), five sets of the 12 ellipses are extracted, then the average values of the five parameters for each ellipse are calculated to suppress detection errors.

5) To detect each cone’s tip and identify which ellipse that detected tip belongs to, we compute each ellipse’s average center of \([\bar{x}_{ep}, \bar{z}_{ep}]\) and average semi-major axis \( \bar{a}_{ep} \) (e.g., the red ellipse in Fig. 9 (d)), where, \( ep \) is the ID number of the twelve cones. In the 2D slice of \( z = \bar{z}_{ep} \), a rectangular ROI (the gray rectangle in Fig. 9 (c)) is estimated, where the ROI’s centerline is the line of \( x = \bar{x}_{ep} \) (the white vertical line in Fig. 9 (c)), and length and width are 510 (the maximum value of the \( y \)-axis) and \( \bar{a}_{ep} \times 2 \), respectively. In the ROI area, the two lines of the edges of the cone are detected using Hough transform, so that the cone’s tip is detected as the crosspoint of the detected two lines. However, sometimes only one edge of the cone can be found (e.g., the rightmost cone in Fig. 9 (c)). In this case, the crosspoint of the detected one edge and the line of \( x = \bar{x}_{ep} \) is detected as the cone’s tip. Similarly, the other cones’ tips are detected. Then the 3D location of each tip in the phantom \( P_{US} \) is decided automatically and precisely from the 3D US volumes.

On the other hand, the position \( P_{hp} \) of each tip in the phantom is manually measured by a pen probe, as shown in Fig. 8, where \( P_{hp} \) denotes the coordinate of each cone’s tip in the 3D tracking space. The calibration matrix \( T_{US2Pr} \), and the reference tracker’s transformation matrix \( T_{Pr2W} \) have the following relationship:

\[
P_{hp} = T_{Pr2W} \cdot T_{US2Pr} \cdot P_{US}
\] (4)

where \( P_{US} = (x, y, z) \), \( x \) and \( y \) are the column and row indices of the pixel on the extracted slice in \( x - y \) plane, and \( z \) is the index of the extracted slice along the \( z \)-axis. The scale factors are integrated with the calibration matrix \( T_{US2Pr} \), therefore, the extra scale factor in the computation is not required. After being multiplied by the inverse of the
reference transformation matrix $T_{Pr2W}$ from left, Eq. (4) can be written as:

$$P_{tip/Pr} = T_{Pr2W}^{-1} \cdot P_{tip} = T_{US2Pr} \cdot P_{US}$$  \hspace{1cm} (5)

where $P_{tip/Pr}$ is a vector in the 3D US probe coordinate system. Considering $n$ positions of the vertices in the phantom, the following equation is obtained from Eq. (5):

$$P_{tip/Pr1, \ldots, Prn} = T_{US2Pr} \cdot \begin{pmatrix} x_1 & \cdots & x_n \\ y_1 & \cdots & y_n \\ z_1 & \cdots & z_n \\ 1 & \cdots & 1 \end{pmatrix}$$

$$= T_{US2Pr} \cdot T_{US}$$  \hspace{1cm} (6)

where $T_{US} = \begin{pmatrix} x_1 & \cdots & x_n \\ y_1 & \cdots & y_n \\ z_1 & \cdots & z_n \\ 1 & \cdots & 1 \end{pmatrix}$. Then, the calibration matrix is calculated by Horn’s method [10], [39], as follows:

$$T_{US2Pr} = (P_{tip/Pr1, \ldots, Prn})^T \cdot (T_{US} \cdot T_{US}^T)^{-1}$$  \hspace{1cm} (7)

5. Experimental Results

5.1 Validation for 3D US Calibration

In practice, a Philips iU22 US system with a V6-2 3D curved-array US probe is employed to collect 3D US data, since curved arrays offer significantly improved sizing than matrix arrays. The Ascension 3D guidance trakSTAR with some Model 90 6-DOF tracking sensors is utilized for tracking. The diameter of the 3D tracking sensor is just 0.9 mm, so that it can be inserted into the surgical tool developed by Zhang et al. [3], whose inner diameter is only 1.0 mm. The static accuracy of the position for the tracking sensor is 1.4 mm RMS and the orientation is 0.5° RMS. Moreover, all programs of each process in C++ run on a quad-core 2.60 GHz computer with 8GB memory.

5.1.1 Calibration Precision

The validation of the calibration is very necessary to evaluate the performance of the 3D US calibration in reconstructing the 3D plane in the tracking space. There are two common evaluation criteria for measuring calibration errors: (1) fiducial registration error (FRE) is the RMS distance between the located position of each fiducial as transformed from the US image space to the tracking space and the position of that corresponding fiducial located in the tracking space, which is used to evaluate how well the EM and US points fit together; (2) target registration error (TRE) is computed in the same manner as FRE, but the points for TRE are not used to estimate the calibration matrix, and thus it provides a better indication of the accuracy of the calibration matrix.

Twenty-four fiducial points from 3D US images and tracking information were recorded, where 12 points are detected from one US volume by using the proposed phantom, and the other 12 points are detected from one more US volume by using the proposed phantom whose base is rotated by 180°. Additionally, 18 points from 3D US images are used for TRE measurement, where nine points are detected from one US volume by using the target model in Fig. 8 (b), and the other nine points are detected from one more US volume by using the same target model with some horizontal translation.

During the calibration, six points (the tips of the phantom from No.1 to No.6) are used initially, increasing by one point at a time up to 24 points (the point is added sequentially as the marked number increases from small to large, where the rotated phantom is marked in the same order) for FRE validation. For each set of calibration points, 18 points based on the target model are used for TRE validation. In total, we record the data of 10 groups (the data of the same experiment for ten times), and each of which corresponds to 24 fiducial points and 18 target points. Additionally, the locations of the nine points phantom during this experiment are different, because we consider the locations of the nine points phantom should be changed horizontally and vertically so that the nine points phantom can cover the entire 3D US space. By doing this, location errors caused by image distortion on distal region of 3D US images can also be included into TRE.

The means and standard deviations of the 10 groups are calculated and illustrated in Fig. 10, with the FREs and TREs at each number of calibration points. As the number ($n$) of calibration points increases, we find that: (1) the means and standard deviations of FREs and TREs have a sudden decrease at $n = 9$ (the first black vertical line in Fig. 10); (2) those values start to converge at $n = 21$ (the second black vertical line in Fig. 10). As a result, the minimum number of the points used for our 3D US calibration system is nine. Moreover, more points (22 or more) do not cause much improvement for calibration results. In that way, 24 fiducial points from two US volumes are chosen to estimate the calibration matrix for locating the 3D fetal model with the oral cavity and airways, and the corresponding FRE of 1.49±0.44 mm and TRE of 1.81±0.56 mm are achieved in this case. On the other hand, though feature extraction is computed in tens of seconds, the overall calibration time of about 6 minutes is mostly due to the manual measurement of the tip of each cone by the pen probe.

![Fig. 10](image-url) The validation results of the 3D US calibration system.
tionship between the internal organs and the 3D fetal facial surface is obtained by measuring TREs in Sect. 5.2.1, although a high accuracy for locating the points on the 3D fetal facial surface can easily be identified manually in 3D US images. The 14 markers are the same hemispheres having a diameter of 5 mm and a height of 2.5 mm (Fig. 11 (a)). The 14 different sizes made by Kyoto Kagaku Co., Ltd, Japan, and they are respectively at the gestational age of 24-weeks (Fetus1), 26-weeks (Fetus2), 28-weeks (Fetus3), 30-weeks (Fetus4), and 32-weeks (Fetus5). A testing database of 60 3D US images are collected by utilizing such five fetal phantoms. The results of the proposed calibration method based on 24 fiducial points are comparable to those obtained by previous calibration methods using EM tracking. The accuracy of our approach is better than the majority of the methods from the comparison in Table 3. Although Lang et al. [8] obtained better accuracy than did our approach, a set of 30–50 volumes is required for each experiment to ensure the best accuracy, which made the calibration process long and tiresome. In conclusion, our system guarantees satisfactorily accuracy, and also only requires a simple experimental setup and two US volumes for 3D US calibration.

5.1.2 Discussion

The results of the proposed calibration method based on 24 fiducial points are comparable to those obtained by previous calibration methods using EM tracking. The accuracy of our approach is better than the majority of the methods from the comparison in Table 3. Although Lang et al. [8] obtained better accuracy than did our approach, a set of 30–50 volumes is required for each experiment to ensure the best accuracy, which made the calibration process long and tiresome. In conclusion, our system guarantees satisfactorily accuracy, and also only requires a simple experimental setup and two US volumes for 3D US calibration.

5.2 Validation for Locating the 3D Fetal Model

In experiments, we use five fetal phantoms with different sizes made by Kyoto Kagaku Co., Ltd, Japan, and they are respectively at the gestational age of 24-weeks (Fetus1), 26-weeks (Fetus2), 28-weeks (Fetus3), 30-weeks (Fetus4), and 32-weeks (Fetus5). A testing database of 60 3D US images are collected by utilizing such five fetal phantoms. For the ICP-registration between the fetal facial surface extracted from the 3D fetal model and 3D US data described in Sect. 3.3, a successful detection rate of 100% is achieved for detecting four key facial features in the coarse registration based on such a testing database, and the achieved mean RMS error of the registration results is 1.04±0.17 mm.

5.2.1 Validation for Locating 3D Fetal Facial Surface

In order to validate location accuracy of the 3D fetal facial surface, 14 silicon target markers are pasted to the frontal facial surface of the fetal phantom, as shown in Fig. 11 (b), where all markers are the same hemispheres having a diameter of 5 mm and a height of 2.5 mm (Fig. 11 (a)). The 14 markers can easily be identified manually in 3D US images (Fig. 11 (c)). Mean TREs of these 14 markers for the test database are experimentally obtained as shown in Table 4, which proves good accuracy of the proposed method.

5.2.2 Validation for Internal Organs

Although a high accuracy for locating the points on the 3D facial surface is obtained by measuring TREs in Sect. 5.2.1, the location of internal organs, i.e., fetal oral cavity and airways, is still difficult. On the other hand, the geometric relationship between the internal organs and the 3D fetal facial surface in the 3D fetal model can be known based on their design. Therefore, we can estimate the corresponding positions of the internal organs in real fetal phantoms via such a geometric relationship.

Herein, as shown in Fig. 12 (a), position P on the bottom of the pharynx and position T on the entrance of the trachea are specified as validation examples, which are considered as the farthest points in the internal organs from the 3D fetal facial surface. The corresponding positions in the real fetal phantom are defined as P’ and T’. Then, an indirect validation method for the location errors of position P and T is proposed as follows:

(1) As shown in Fig. 12 (b), three positions, n0, n1, and n2 are specified manually as reference points on the surface of the 3D fetal model, where n0 is the position of the nose tip, and n1 and n2 are the positions of the two eyes’ inner corners;

(2) Let v′i (i ∈ {1, 2}) be the vectors from n0 to n1, and let vP be the vector from n0 to position P. Since the selected three positions and P position can be known from the design of the 3D fetal model, θ_i (i ∈ {1, 2}), which are the angles between vP and v′i, are computed. Meanwhile, the cross product v2 × v1 is defined as a vector v2×1 that is perpendicular to both v2 and v1, with a direction given by the right-hand rule. Then, θ_p, which is the angle between vP and v2×1 is computed;

(3) The corresponding three positions n′i (i ∈ {0, 2}) on the surface of the real fetal phantom in 3D tracking space are directly measured by the pen probe prior to experiments. The vectors v′i (i ∈ {1, 2}) from n′0 to n′1 and v′2×1, which is the cross product v′2 × v′1, are computed, as shown in Fig. 12 (c). Since the geometric relationship among the selected three

### Table 3 Comparison of the results of previous studies and our approach.

| Methods          | Results (RMS) |
|------------------|---------------|
| Lange and Eulenstein | 3.3 mm        |
| Huang et al.     | FRE: 1.23±0.26 mm, TRE: 2.37±0.81 mm |
| Parthasarathy et al. | 2.2±1.8 mm   |
| Lang et al.      | 1.39±0.54 mm  |
| **Our approach** | FRE: 1.49±0.44 mm, TRE: 1.81±0.56 mm |

### Table 4 Mean TREs of each phantom (mm).

| Fetus | TRE (mm) |
|-------|----------|
| Fetus1 | 1.52±0.32 |
| Fetus2 | 1.75±0.43 |
| Fetus3 | 1.64±0.39 |
| Fetus4 | 1.58±0.64 |
| Fetus5 | 1.44±0.50 |

**Mean TRE for all fetuses**: 1.55±0.46
positions \( n_i \) \((i \in [0, 2])\) and position \( P \) in the 3D fetal model is the same as that among the corresponding three position \( n_i' \) \((i \in [0, 2])\) and position \( P' \) in the real fetal phantom, the following relationships hold.

\[
v_i' \cdot v_p' = |v_i'| \cdot |v_p'| \cdot \cos \theta_i, \ i \in [1, 2]
\]
\[
v_{2\times1}' \cdot v_p' = |v_{2\times1}'| \cdot |v_p'| \cdot \cos \theta_p
\]
\[
\frac{|v_i'|}{|v_p'|} = \frac{|v_{1}|}{|v_p|}
\]

where, \( \theta_i \) \((i \in [1, 4])\) and \( \theta_p \) are calculated in step (2), and the coordinate \((x, y, z)\) of position \( P' \) in 3D tracking space are the solutions of the above simultaneous equations from Eq. (8) to Eq. (10). Thus, a unique solution of \((x, y, z)\) is computed as a ground truth for estimating the position \( P \).

On the other hand, the estimated coordinates of the position \( P \) from the 3D fetal model are transformed into the 3D tracking space based on the ICP-registration matrix and 3D US calibration system. Then, the transformed coordinates in the 3D tracking space of the position \( P' \) are compared with the ground truth (the estimated coordinates of \( P \)) to calculate its location error. Similarly, the location error of position \( T \) can also be estimated. As a result of experiments, the mean location errors of the position \( P \) and \( T \) for the testing database are 2.51±0.47 mm and 3.04±0.59 mm, respectively, as shown in Table 5.

In addition, for FETO surgeries, the surgical tool having an outer diameter of 2.4 mm is inserted into fetal airways until the tool reaches the entrance of fetal trachea. During this procedure, the narrowest part of the passage is the fetal pharynx, through which the surgical tool is supposed to go. The FETO surgery is normally performed at about 26–29 weeks gestational age (GA); therefore, the average diameter of fetal pharynx is 7.7 mm at that time. Thus, 5.3 mm \((= 7.7 - 2.4)\) mm is the maximum tolerance for this surgery. Consequently, both of the location errors of the pharynx (2.51±0.47 mm) and the entrance of the trachea (3.04±0.59 mm) satisfy the requirement of the FETO surgery.

5.3 Efficiency of the Surgical Navigation System

In the online process, there are several factors contributing to the final efficiency of the surgical navigation system: (1) the extraction of 3D fetal facial surface from 3D US data (Step-1); (2) ICP-based registration, including key facial feature detection (Step-2); (3) 3D US calibration-based transformation (Step-3). The mean execution time of each key step for 10 groups of five fetal phantoms are listed in Table 6, which shows the system spends about 16911±469 ms on the location of 3D fetal facial surface and internal organs. On one hand, the fetus is supposed to be immobilized during the FETO operation [2]. Once the registration is realized before the operation, no more registration is required during the operation so that real-time 3D registration is not necessary for the surgery. On the other hand, compared with 221±69 minutes, which is medical doctors’ average time for FETO surgeries [40], the time of the navigation system is very short and thus should meet current requirement of the FETO surgery.

However, the current survival rate in fetuses with left-sided CDH (the majority of hernias (80–85%) occur on the left side of the diaphragm) treated with the FETO surgery is not so high: the specific survival rate is between 24.1% and 49.1% [2]. Therefore, reducing the surgery time might be one solution to raise the survival rate. Thus, a faster computation speed of the surgical navigation system could contribute to such a solution; in other words, faster computations are always demanded.

In addition, we can learn that Step-1 spends the most time \((15906±341\text{ms})\) during the online process, which is a major factor deciding the final efficiency of the system. However, the efficiency of Step-1 can easily be increased by 50–100 times based on the technology of multi-threaded processing and multi-core processors. The efficiency of Step-2 and Step-3 can also be increased by 10–50 times based on GPU technology. Consequently, the computation time of the system can be improved to be less than one second in the future by making use of algorithm optimization, multi-threaded processing, multi-core processors, and GPU technology.

6. Conclusions

This paper has proposed an approach for accurately locating 3D fetal facial surface, oral cavity, and airways based on the registration between the 3D fetal model and 3D US images and a real-time 3D US calibration system. The reconstructed 3D fetal model with the oral cavity and airways is registered with the 3D US images extracted from 3D US images and located in 3D US space. Then, the 3D US calibration system based on a novel cones’ phantom is proposed to transform the 3D fetal model from the 3D US space to the 3D tracking space, and a FRE of 1.49±0.44 mm and a TRE of 1.81±0.56 mm by using 24 fiducial points from two US volumes are achieved. Furthermore, a mean TRE of 1.55±0.46 mm is achieved for measuring location accuracy of the 3D fetal facial surface extracted from 3D US images by 14 target markers, and mean location errors of 2.51±0.47 mm and 3.04±0.59 mm are respectively achieved for indirectly measuring location accuracy of the pharynx and the entrance of the trachea, which satisfy the requirement of the FETO surgery.

In the future, we will introduce more points (e.g., some
3D points on the fetal body) to reduce the error of ICP-based registration. Furthermore, the location of the surgical tool and the feedback from fetoscopic video sequences will be included in the surgical navigation system to make a comprehensive evaluation. Clinical fetal MR images are also essential for directly validating the location errors of the fetal oral cavity and airways, and will be considered in the cooperation with some hospitals.

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