Augmenting interventional ultrasound using statistical shape model for guiding percutaneous nephrolithotomy: Initial evaluation in pigs

Zhi-Cheng Li\textsuperscript{a,b,*}, Kai Li\textsuperscript{c}, Hai-Lun Zhan\textsuperscript{d}, Ken Chen\textsuperscript{a}, Ming-Min Chen\textsuperscript{a}, Yao-Qin Xie\textsuperscript{a}, Lei Wang\textsuperscript{a}

\textsuperscript{a} Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China
\textsuperscript{b} Beijing Center for Mathematics and Information Interdisciplinary Sciences, Beijing, China
\textsuperscript{c} Department of Medical Ultrasonics, The Third Affiliated Hospital of Sun Yat-sen University, Guangzhou, China
\textsuperscript{d} Department of Urology, The Third Affiliated Hospital of Sun Yat-sen University, Guangzhou, China

\textbf{Abstract}
Successful percutaneous nephrolithotomy (PCNL) highly depends on an accurate needle puncture of the kidney. This puncture step is challenging and must be performed under intraoperative image guidance. This paper presents an image guidance method for PCNL by augmenting interventional ultrasound (US) using a 3D statistical kidney model. First, a 3D statistical kidney model is built a priori from a collection of aligned training shapes. Intraoperatively, a patient-specific 3D kidney model is reconstructed in a fine-tune way using sparse manually picked points from calibrated US at maximum exhalation. The US images are then augmented with the kidney model and a real-time tracked virtual needle. Under the augmented-US guidance, percutaneous renal puncture can be performed. Experimental results based on Wuzhishan pig data have validated the accuracy and inter-operator repeatability of the presented kidney model reconstruction. The feasibility and efficiency of the proposed augmented US-guided puncture for PCNL have been demonstrated in pigs. With careful setup by trained surgeons, our proposed guidance has the potential to reduce the occurrence of complications such as PCS access failure and bleeding compared with a traditional US-guided method.

\section{Introduction}

Since its first introduction by Fernström and Johansson in 1976 \cite{1}, percutaneous nephrolithotomy (PCNL) has been continually evolving for three decades and currently established itself as an important minimally invasive treatment option for removal of large and complicated kidney stones \cite{2}. Optimal outcomes of PCNL highly depend on an accurate percutaneous renal access, i.e., an accurate needle puncture from the skin to the pelvicaliceal system (PCS). Intraoperative image guidance is crucial for a successful percutaneous renal access, because needle puncture without image guidance is imprecise and an injury to vital structure could take place \cite{3}.

In the clinical routine, the needle puncture in PCNL is often performed under the guidance of radiographic fluoroscopy or interventional ultrasound. Fluoroscopic guidance can provide real-time projective images of both the collection system and the contained stones \cite{3}. The main disadvantages include the harmful radiation exposure for patient and medical personnel and the cumbersome handling when projecting from various orientations. The ultrasound (US) can provide dynamic sectional images and has been proven to be a good alternative as its radiation-free, portable and easy-to-use \cite{4}. However, the abdominal US is often related to limited anatomy identification and localization abilities, as it provides only 2D anatomical information with indistinct anatomic landmarks. Other techniques for aiding PCNL such as robotic system (for example, the PAKY) and C-arm system were also reported \cite{5,6}. Currently, new image guidance techniques for renal access in PCNL with explicit anatomy identification and accurate target localization are still on demand.

One promising technique is to augment the intraoperative image (US, fluoroscopy, or video) with preoperatively obtained information, such as preoperative computed tomography (CT) or magnetic resonance (MR) images, anatomic models, or planned needle tract \cite{7}. This so-called image fusion navigation technique attempts to provide surgeons with more accurate localization and more intuitive visualization. Recently, the navigation technique

\textsuperscript{*} Corresponding author. No. 1068 Xueyuan Avenue, Shenzhen University Town, Shenzhen 518055, China.
E-mail address: zc.li@siat.ac.cn (Z.-C. Li).

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has gained increasingly recognition especially in neurosurgery and orthopedics, in which the target organs can be assumed to be rigid and have legible anatomical landmarks [8].

Several navigation techniques for kidney intervention have been presented. For example, the authors in [9,10] proposed a system to guide the percutaneous renal puncture by fusing the intraoperative US and preoperative CT or MR. A navigation device that projects a virtual needle of the US puncture tract onto fluoroscopic images has been recently evaluated [11]. In our previous work [12], we proposed a surgical planning and navigation system for renal intervention by augmenting the US with preoperative planning models and real-time tracked needle. We further developed an image-guided robotic-assisted system to perform accurate renal punctures [13]. Advantages of these techniques include GPS-like real-time navigation, intraoperative 3D perception, and visualized surgical planning. On the other hand, successful renal navigation highly relies on an accurate registration between the preoperative data and the intraoperative patient [8]. Such registration is challenging because the position and shape of kidney change since preoperative imaging due to organ shift and tissue deformation. Moreover, the navigation-based renal intervention requires complicated workflow including at least preoperative imaging and intraoperative registration. The operation time therefore becomes longer and substantial training may be required. Thus the overall cost will increase. These drawbacks to some extent prevent this technique from wide clinical use [14].

Our motivation is to overcome the aforementioned drawbacks by providing real-time navigation and 3D anatomy visualization in the absence of preoperative CT or MR. The aim is to aid the needle puncture in PCNL. To this end, we attempt to build a patient-specific 3D kidney model from intraoperative 2D US images. It is a challenging task, because the kidney boundary is often fuzzy, diffused, and incomplete in US images. Further difficulty arises when building a 3D kidney model from 2D US. Since the kidney edge and region cues are often unreliable in US, prior shape knowledge is often incorporated [15]. A widely recognized approach to incorporate the shape priors relies on the use of a statistical shape model (SSM) [16]. In SSM, shape variations of the target anatomy are efficiently parameterized from a collection of training samples with correct landmark correspondence. The key task of SSM-based anatomy reconstruction is to search from the parameterized shape space an optimal instance that best fits target anatomy. The target anatomy is usually represented by sparse input data such as point cloud or contour lines extracted from intraoperative images.

There have been several studies on the SSM-based 3D anatomy reconstruction from sparse input data. According to the intraoperative image modalities used, existing methods can be categorized into X-ray-based and US-based approaches. The X-ray-based approaches focus on reconstructing bony anatomy surfaces, such as the 3D femur and pelvis [17,18]. In the area of SSM-based US anatomy reconstruction, most research focus on organs with high-contrast US interface, such as bone [19], prostate [20] and cardiac structures [21]. Although the techniques developed in these studies provide inspirations for fitting the SSM to the sparse data, they cannot be used straightforwardly to the 3D kidney model building for the purpose of renal puncture in PCNL. A task-specific method is still in demand. To the best of our knowledge, no research groups have attempted to guide renal puncture by augmenting interventional US using 3D SSM.

The purposes of this paper were (1) to propose an image-guided renal puncture for PCNL by augmenting interventional US using the 3D statistical kidney model, and (2) to evaluate the feasibility and efficiency of the proposed method in pig models. The rest of the paper is organized as follows. Section 2 describes the proposed image-guided intervention in detail. Section 3 evaluates the proposed methods via experiments in pig models. Section 4 presents the results and discussions. Section 5 concludes the paper.

2. Methods

2.1. Overview of the proposed intervention

The overview of the proposed augmented US-guided intervention is illustrated in Fig. 1. First, a 3D statistical kidney model is built a head from a collection of aligned training shapes. Intraoperatively, a patient-specific 3D kidney model is built from a few manually picked points from the US images. The US images are then augmented with the kidney model and a real-time tracked needle. Under the augmented-US guidance, percutaneous renal puncture can be performed. The proposed system comprises a diagnostic ultrasound device, an optical tracker, a tracked puncture needle, and a computer. Main features of the proposed method are as follows.

(1) Patient-specific 3D kidney model and real-time tracked needle are superimposed onto the intraoperative US images, in

![Diagram](https://via.placeholder.com/150)

**Fig. 1.** Overview of the proposed image-guided intervention workflow.
order to enhance the surgeon’s perception and improve the target anatomy location.

(2) No CT or MR imaging is required, and no complicated intraoperative registration is required. Therefore, the work flow change is limited and the entire intervention is radiation-free and low-cost.

(3) The kidney model building and US image augmentation can be finished quickly. This feature allows online refine of the result by picking more points or removing unsatisfied points.

Next, we will describe in detail the proposed intervention technique.

2.2. Statistical shape model building

The first step is to build a 3D SSM of kidney from an input training database. In this work, the input dataset comprises a group of kidney surfaces described by triangular meshes. The data acquisition method will be described in Section 3.1.

In SSM building, a critical issue is to establish a dense spatial correspondence across all training shapes. We use a fully automatic approach to determine the correspondence. First, in order to efficiently manipulate the correspondence points (landmarks) on the kidney surface, each surface is parameterized by mapping the surface mesh onto a unit sphere using a conformal mapping [22]. A Procrustes analysis is used to initialize the scale and pose of all shapes [16]. Then, the parameterization is optimized using a gradient descent method based on simplified minimum description length (MDL) criteria [23]. Finally, all shapes are aligned and each contains 3612 landmarks distributed equally over the kidney surface.

Let \(x = (p_1, p_2, \ldots, p_n)^T\) denote the j-th shape, where \(p_k \in \mathbb{R}^3\) is the Cartesian position vector of the i-th landmark, \(N\) is the landmark numbers. Taking \(x, j = 1, \ldots, M\) as column vectors, we then obtain a landmark configuration matrix \(C = [x_1, x_2, \ldots, x_N]\), where \(M\) is the number of training shapes. Applying principal component analysis (PCA) on matrix \(C\), we obtain the principal modes of the variation of training shapes, i.e. the eigenvectors \(p_k\) of the shape covariance matrix, \(k = 1, 2, \ldots, m, m \leq M - 1\). The eigenvectors \(p_k\) are sorted by their corresponding eigenvalues \(\lambda_k\) in descending order. The \(m\) mutually orthogonal eigenvectors \(p_k\) span a shape space \(\Omega\) with the mean shape as its origin. Any shape instance in this eigenspace can then be described by the mean shape and a linear combination of the eigenvectors

\[
x = \bar{x} + \sum_{k=1}^{m} b_k p_k,
\]

where \(\bar{x} = (1/M)\sum_{x} x_k, b_k \in \mathbb{R}\) is the weight factor that controls the \(k\)-th shape variation mode. So far, a 3D SSM of the kidney has been established. Note that, in order to aid the alignment in next step, three landmarks on the cranial pole, the caudal pole and the center of the renal hilum, represented as \(m_1, m_2, m_3\) respectively, are manually labeled on the mean kidney shape. Fig. 2 shows the shape variations of \(\pm 2\) standard deviations captured by the first mode of the kidney model.

2.3. Kidney model reconstruction from US

This subsection describes how to reconstruct a kidney surface from US images. In this work, a US machine (Mindray DC-7, Shenzhen, China) with a 3.5 MHz abdominal probe was used. The US probes were mounted with optically tracked reflective markers such that the probe position can be read in real-time by an optical tracker (Northern Digital Incorporation, Waterloo, Canada). The navigation starts with the US calibration process. A built-in calibration application provided by Mindray helps to transform the US image pixel positions to the local 3D space relative to the probe. The further transformation from the local 3D space to the world coordinate system defined by the tracker can be calculated directly based on the tracker’s real-time output. Finally, all US slices can be calibrated and located in the tracker space. Details about the calibration were described in our previous work [12].

On the other hand, organ motion due to the respiration could induce inconsistency between the positions of the target anatomy in different US slices. Therefore, we expect to acquire US slices at the same stages of the respiration cycles. It has been shown that for free respiration the kidney assumes the same positions at equivalent lung volumes [24]. Moreover, the end-exhale represents the longest natural pause in a cycle [25]. Thus, we expect to use only US slices at the maximum exhalation (ME) positions.

In such a case, calibrated US images that contain clear kidney contours at ME positions can be selected. From the selected images, the points on the kidney contour can be manually picked according to the following three principles. First, three landmarks on the cranial pole, the caudal pole and the center of the renal hilum must be selected and labeled for future use in alignment initialization. Second, all selected landmarks must be on distinct and recognizable kidney contours in order to guarantee the reliability. Third, the landmarks should be distributed as evenly as possible over the kidney surface. The obtained sparse points can be represented as a vector \(s = (s_1, s_2, \ldots, s_N)^T \in \mathbb{R}^N\), where \(s_i\) denotes the 3D position vector of the i-th point, \(N \leq N_s\). Let the first three points \(s_1, s_2, s_3\) denote the three landmarks for alignment initialization. Note that for experienced operators the three landmarks can be quickly identified in only a few US slices. That is why they were chosen for pose initialization.

Assume that the to-be-reconstructed kidney shape \(x^*\) is in space \(\Omega\). Based on Eq. (1), the unseen shape \(x^*\) can be expressed as \(\bar{x} + \sum_{i=1}^{m} b_i^* p_i\). Therefore, the problem can be formulated as looking for a weight factor vector \(b^* = (b_1^*, b_2^*, \ldots, b_m^*)\) that minimizes the distance between the target shape \(x^*\) and the sparse points \(s\). The problem is solved using the following two-step method consisting of rigid registration and SSM instantiation.

![Fig. 2.](image-url) The first mode of \(\pm 2\) SD variations of the statistical kidney model. SD represents standard deviation.
The reconstruction starts with the rigid registration of the sparse point set $s$ and the mean shape $\mathbf{X}$. This can be accomplished by a point-to-point registration technique such as an iterate closest point (ICP) algorithm that minimizes the mean square distance between them [26]. However, ICP is sensitive to the initial pose and could be prone to fall into local minima, especially for noisy point sets. Therefore, an initial alignment is performed based on three pairs of landmarks on the cranial pole, the caudal pole and the center of the renal hilum. The three landmarks from the US are $s_1, s_2, s_3$. Their corresponding landmarks from the mean shape are $m_1, m_2, m_3$ mentioned in the previous subsection. Note that a coarse initial alignment is enough for ICP therefore we do not require precise correspondence between the two pairs of landmarks. The initial alignment can be calculated by a simple corresponding points registration. Based on the initial pose and scale, the corresponding points registration, i.e. the rotation $R$, translation $T$, and scale $S$, is then calculated using the ICP algorithm. Therefore, the point set can be registered to the statistical kidney model as

$$s' = s_1^i = (S \cdot R \cdot s_1 + T), \quad i = 1, 2, ..., N'. \quad (2)$$

After the rigid registration, the next task is to extrapolate a patient-specific kidney surface mesh from the sparse points by statistical instantiation of the SSM. Based on the ICP result, the corresponding closest point set of the sparse point set $s$ on the mean shape $\mathbf{X}$ can be known. Let $j = c(i)$ denote that the $j$-th point on $\mathbf{X}$ is the closest point corresponding to the $i$-th input point $s_i$, where $c(\cdot)$ is the correspondence operation. Then, we can reconstruct a “sparse shape” $\mathbf{x}'$ containing $N'$ vertices by

$$\mathbf{x}' = [x'_j] = [X_j + \sum_{k=1}^{m} b_k p_k(j)].$$

$$j = c(i), \quad i = 1, 2, ..., N', \quad (3)$$

where $X_j$ denotes the 3D position of the $j$-th point on $\mathbf{X}$, and $p_k(j)$ denotes the $j$-th tuple of $p_k$. Our next task is to extrapolate the sparse mesh $\mathbf{x}'$ containing $N'$ vertices to be a complete mesh $\mathbf{x}^*$ containing $N$ vertices. To this end, we search for an optimal weight vector $b^*$ for the complete mesh $\mathbf{x}^*$ such that the distance between $\mathbf{x}^*$ and $\mathbf{s}'$ can be minimized. On the other hand, $\mathbf{x}^*$ should have a similar shape to the mean shape $\mathbf{X}$. In such a case, this statistical instantiation problem can be formulated as a least squares error minimization with regularization terms [17]. The object function to be minimized can be defined as

$$F(b^*) = \alpha \cdot \sum_{i=1}^{N'} \| s'_i - x'_i \|^2 + \sum_{k=1}^{m} \left( \frac{b_k^2}{\lambda_k} \right). \quad (4)$$

where $j = c(i)$. Here the Euclidean distance (the first term) between two corresponding point sets $\mathbf{x}'$ and $\mathbf{s}'$ is used to measure the fitting quality of $\mathbf{x}'$ and $\mathbf{s}'$. The Mahalanobis distance (the second term) between the $\mathbf{x}^*$ and the mean shape $\mathbf{X}$ presents a prior shape constraint and is used to penalize possible overfitting that could lead to an implausible kidney shape. $\alpha$ is a factor that controls the weighting of the fitting term and constraint term. Larger $\alpha$ means more freedom while smaller $\alpha$ means more prior constraint. In this paper $\alpha$ was empirically set to 3 and was found effective in all tests. $\lambda_k$ denotes the $k$-th eigenvalue of the shape covariance matrix, as mentioned in Section 2.2. To solve the minimization problem, let the differentiations of $F$ with respect to $b_k^2$, $i = 1, ..., m$, be equal zero such that a linear equation system can be formed. Each $b_k^2$ can then be calculated directly by solving linear equations and thus the kidney shape $\mathbf{x}^*$ can be known based on Eq. (1). In our study, all non-zero eigenvectors were used to instantiate the unseen shape without observably increasing the computation time.

The obtained 3D point set $\mathbf{x}^*$ still needs triangulation to be used for surface rendering in visualized navigation. In this study, a crust algorithm was used to generate a triangulated tight surface based on the dense point set $\mathbf{x}^*$ [27]. Then, a ball pivoting based manifold extraction was performed to output a regular surface.
This regular surface mesh is the final reconstructed kidney model.

2.4. Augmented US guided puncture

Based on R, T and S, the reconstructed kidney model can be transformed to the tracker’s space. The needle position can be precisely measured by the tracker in real time and fused in the visualized guidance as a virtual needle. Finally, the intraoperative image guidance is provided by augmenting the US images with the kidney model and the virtual needle.

The guidance interface consists of four views, as shown in Fig. 3. The left top view fuses the US images, the 2D projection of the kidney model onto the US image plane, and the virtual needle. The right top view represents the US image superimposed with a virtual needle. In the left bottom, the US image, the 3D kidney model and the virtual needle are provided. The right bottom view plots the real-time respiratory gating curve. Because the reconstructed model represents the kidney shape at ME position, the image-model fusion accuracy cannot be guaranteed at the other stages of the respiratory cycle. Therefore, we expect to perform the renal puncture at ME position. The ME positions can be detected by visual inspection of the surgeon on the real-time respiratory gating curve. Because the reconstruction was evaluated using leave-one-out cross-validation, the reconstructed kidney model can be finished quickly (typically less than 2 s for 90 input points in our experiment). Therefore, the kidney model reconstruction can be performed in a fast fine-tuning way as follows. Assume that a kidney model has been reconstructed from several points and displayed. If the surgeon is satisfied with the result after a visual quality check, he can perform the puncture under the image guidance. Otherwise, he is allowed to refine the reconstruction by picking new points or removing already-picked points. Based on the previous computation result, the kidney model can be updated and displayed very quickly after adding or removing one points. Note that if the model initialization landmarks, i.e. points on the cranial pole, the caudal pole and the renal hilum center, are modified, all previous reconstruction results should be ignored and a kidney model have to be reconstructed from scratch. The completed workflow of the proposed image-guidance intervention is shown as follows.

1. Calibrate the optical tracker and the US machine.
2. Acquire US images at ME positions using the respiratory gating.
3. Pick several points from the kidney contours in US images. An initial kidney model is displayed.
4. Refine the kidney model in a fast fine-tune way by picking more points or removing unreliable points until be satisfactory with the result.
5. Perform the renal puncture under the augmented US guidance.

3. Experiments

First, the accuracy and repeatability of the kidney model reconstruction was evaluated using leave-one-out cross-validation. The effects due to training population size were also evaluated. Then, the feasibility and efficiency of the proposed image-guided PCNL were assessed in pigs models.

3.1. Animals and data acquisition

The morphometric and anatomic features of the pig kidney, such as size, shape, PC system, are similar to those of human kidney [29]. Pig kidneys are frequently used models for training PCNL [30,31]. In our experiment, 28 Chinese Wuzhishan pigs with a mean weight of 26 ± 4 kg were used as the animal models. All pigs were numbered in sequence. Sex was not considered as the male pigs were castrated. Approval from institutional animal review committee was obtained.

From March 2012 to January 2013, all 28 pigs underwent abdominal MR imaging of both kidneys on a Siemens MAGNETOM Trio Tim 3.0-tesla machine with the same sequence (TR/TE 4.23/ 1.91 ms, slice thickness 1.25 mm, field of view 147 mm × 210 mm, matrix 160 × 112, flip angle 9°, no interslice gap). Before MR imaging, the animals were anesthetized with xylazine (2 mg/kg body weight) and intraperitoneal pentobarbital sodium (25–30 mg/kg body weight). One MR image obtained in December 2012 was shown in Fig. 4. The MR volume data was then transferred and stored in a workstation. An expert radiologist was asked to segmented both right and left kidneys in a slice-by-slice manual tracing way. A morphological closing followed by a flood-fill operation was performed to close holes. Each binary segmentation was then smoothed using a 3D Gaussian kernel and converted to a triangular surface mesh using a Marching Cubes algorithm. Each kidney surface was decimated to contain approximately 2600 vertices. The obtained dataset was separated into the left kidney subset and the right kidney subset (each contains 28 surface meshes) and used as the SSM training dataset. In this work, all SSMs were built using the method described in Section 2.2 and represented as dense triangular meshes containing 10,242 vertices.

The US images for each anesthetized pig were acquired using a Mindray DC-7 machine with a 3.5 MHz abdominal probe and transferred to the workstation. Using the aforementioned calibration and respiratory gating techniques, 15–25 US slices were
selected at ME positions from each kidney, covering from transverse to longitudinal views of the kidney. Sparse points can be manually picked by a cursor from the kidney contours in selected US images. The picked points were used as input of the kidney reconstruction. The workstation used in our experiments was Dell Precision T5600 with an Intel Xeon 3.30 GHz CPU and 4 GB 1600 MHz RAM.

3.2. Leave-one-out validation

Leave-one-out validations were carried out to evaluate the accuracy and repeatability of the kidney model reconstruction. Note that the SSM for left and right kidneys was modeled separately. In one round of validation, all 28 left (right) kidneys were partitioned into two complementary subsets: the training subset containing 27 kidneys and the testing subset containing the left-out 1 kidney. A SSM was constructed from the training subset using the method described in Section 2.3. In order to evaluate the inter-operator repeatability, two surgeons (K.L. and H.-L.Z.) who were experienced in interventional urology were asked to pick a number of points from the left-out kidney contours in US images. To prevent bias, each surgeon was blind to the results obtained by the other.

Then, the sparse points obtained by each surgeon were extrapolated to be a 3D kidney model using the SSM obtained from the training subset. To evaluate the effect of point number, for each kidney nine surface models were reconstructed using 20, 30, 40, 50, 60, 70, 80, 90 and 100 points picked by each surgeon. Note that for each given input point number, the surgeons were allowed to reconstruct a kidney model in the fine-tune way described in Section 2.4. The MR surface mesh of the left-out kidney was registered to the reconstructed model using ICP. The registered MR surface was used as the gold standard. Root mean square (RMS) distance from each constructed model to its gold standard was calculated as accuracy criteria. 28 rounds of validations were performed for left (right) kidney and the mean accuracy was calculated over all rounds. The time for point picking were also recorded without prior informing the surgeons.

3.3. Influence of training population size

To assess the influence of the training population size, two training sets were used. The small one included the 1st–12th pigs, while the large one included the 1st–22nd pigs. The left and right kidneys were considered separately. Based on the large and small training sets, two SSMs were built. The testing set included the 23rd–28th pigs. One surgeon (K.L.) was asked to pick a number of points from US images for each pig in the testing set. Then, the sparse points from each pig were used to reconstruct two kidney models, using the two aforementioned SSMs. Based on each of the two SSMs, nine surface models were reconstructed for each testing kidney in the fine-tune way using 20, 30, 40, 50, 60, 70, 80, 90 and 100 points. RMS distance from each reconstructed model to its registered-MR gold standard was calculated.

3.4. PCNL experiments on pigs

The aim is to validate the feasibility and efficiency of the proposed intervention in PCNL. The proposed image-guided PCNL experiments were carried out on the left kidneys of the 23rd–28th pigs. For comparison, traditional US-guided PCNL was carried out on the right kidneys of those pigs. SSM for the left kidney was built using the MR surfaces obtained on previous 22 pigs. There were two surgeons in this experiments. One (K.L.) performed the proposed and traditional PCNL experiments on the 23rd–25th pigs, while another (H.-L.Z.) carried out the comparative studies on the 26th–28th pigs. The 20th and 21st pigs were used for validation.
Before the surgery, food was withheld for 15 h. All interventions were performed under anesthesia using xylazine (2 mg/kg body weight) and intraperitoneal pentobarbital sodium (25–30 mg/kg body weight). The animal was first arranged in the supine position. A 5F ureteral catheter (COOK Medical, Bloomington, IN) was inserted from the ureter into the left kidney pelvis with the assistance of a 0.038 inch guidewire (COOK Medical, Bloomington, IN) and a ureteroscope (Richard Wolf, Knittlingen, Germany). Saline was instilling through the ureteral catheter to produce mild hydro nephrosis. In the 28th pig the catheter inser- tion was failed. Alternatively, furosemide was injected intrave- nously to dilate the collecting system.

Then, the animal was placed in dorsal lithotomy position. First, an augmented US-guided percutaneous puncture was performed on the left kidney with the 18-gauge trocar needle (COOK Medical, Bloomington, IN) into PCS. Note that the surgeons were allowed to reconstruct the kidney model in a fine-tune way and decide how many points were used by means of visual quality check of the 3D rendered model. The trocar needle was mounted with reflective markers such that the needle tip can be tracked after calibration. Because the collecting system was filled with saline, fluid efflux out of the trocar was seen as the sign of a successful puncture to PCS. Otherwise, it was considered as a PCS access failure and the surgeon needed to puncture again. Similarly, a US-guided percu- taneous puncture was performed on the right kidney. The proce- dure time, PCS access failure, complications such as bleeding and infection for both kidneys were recorded. The surgeons were not informed what data would be recorded. The environment of the PCNL experiment is shown in Fig. 5.

A scoring system proposed in our previous work [12] was used to rate the proposed intervention. Specifically, the surgeons scored the proposed techniques in terms of three criteria as follows. Intervention Improvement from 5 to 1 respectively denotes sig- nificant, meaningful, moderate, fair, and little localization improvement by using the proposed guidance. Workflow Impact indicates the acceptability of the proposed workflow, where 5 to 1 respectively denote positive, acceptable, acceptable after training, acceptable with reluctance, and unacceptable. Clinical Rele- vance denotes the clinical value of the proposed guidance, where scores 5 to 1 correspond to values of high, moderately high, medium, moderately low to low. The surgeons were allowed to rate x.5 that represents an assessment between x and x + 1.

4. Results

4.1. Leave-one-out validation results

Several left kidney models of the 25th pig reconstructed by surgeon K.L. are shown in Fig. 6. Fig. 6(a) shows the gold standard kidney surface derived from MR data. Fig. 6(b–d) shows the reconstructed surfaces with color-coded distance maps using different numbers of input points. The color-coded distance was calculated using an open source tool MESH to measure Hausdorff’s distance between the reconstructed surface mesh and its gold standard [32]. The error distribution is shown in the left color bar. The RMS distance was respectively 1.93 mm, 1.11 mm and 0.64 mm for kidney models reconstructed using 30, 50 and 90 input points.

The mean reconstruction error with the standard deviation against different numbers of input points is plotted in Fig. 7(a,b). It clearly shows that the mean RMS error reduces with more input points. The two curves representing the mean error for the two surgeons are close to each other. Let us take the left kidney for examples. For surgeon K.L., the mean RMS error was 1.76 mm for 30 input points and reduced to 0.94 mm for 100 input points. For surgeon H.-L.Z., the mean RMS error was 1.88 mm for 30 input points and reduced to 0.98 mm for 100 input points. It can be observed that the standard deviation for both surgeons reduces as the input points increase. For the left kidney reconstructed by surgeon K.L., the standard deviation was 0.63 mm for 20 input points and reduced to 0.22 mm for 100 input points. The differ- ences of the mean reconstruction error between the two surgeons are shown in Fig. 7(c,d). It can be found that the absolute difference was tend to decrease with more input points. For example, for the left kidney the difference was 0.13 for 30 input points and reduced to 0.05 for 100 input points. The mean reconstruction difference over all input point numbers was 0.09 mm for the left kidney and 0.10 mm for the right kidney. Furthermore, we observed that in the case of less than 50 input points, the reconstruction error decreased quickly if we input more points. While in the case of more than 60 input points, the reconstruction error decreased slowly or even almost kept unchanged when adding more points.

The mean time for point-picking and computation for both surgeons was presented as stacked bars in Fig. 8(a) and (b) respectively. Note that the mean time was obtained by averaging all data for both kidneys. It can be found that the point-picking time and computation time were similar for the two surgeons. From Fig. 6(a), we observe that it took less than 5 min for both surgeons to pick 100 points. From Fig. 6(b), it can be found that most computation time was spent on the ICP registration. Typi- cally, the total computation time for both surgeons was less than or equal to 2 s for ≤100 input points.

4.2. Results for different training population sizes

The mean reconstruction error against different numbers of input points is plotted in Fig. 9. It shows that in our experiments SSM built from large training population provided more accurate reconstruction results than that built from small ones. For the left kidney, the mean error for 30 input points was 2.14 mm using large training population and 2.99 mm using small training population. For the right kidney, the mean error for 90 input points was 1.06 mm using large training population and 1.46 mm using small training population. The mean reconstruction differ- ence over all input point numbers was 0.50 mm for the left kidney and 0.49 mm for the right kidney.

4.3. Results for PCNL experiment on pigs

The number of picked points and corresponding reconstruction error for the left kidney model used in PCNL tests are listed in Table 1. The average number of points used for model reconstruc- tion was 80.3. The average point-picking time was 267 s. The average RMS error for the left kidney was 1.00 mm. The results for the two surgeons were similar. The comparison of the proposed and traditional PCNL in terms of the entire operation time, access failure rate and complications is listed in Table 2. We can first find that no complications occurred in all augmented US-guided PCNL trials. Bleeding was observed in tradition PCNL trials in the right kidneys of the 23rd, 26th and 27th pigs. Mild infection was found in the 26th pig. No access failure occurred in pigs underwent the proposed PCNL. However, there were totally twice access failures in pigs under- went traditional PCNL. The average failure rate over all punctures in the traditional PCNL trials was 25%. The average operation time for proposed and traditional PCNL trials was 11.9 min and 6.9 min. The subjective scoring results are shown in Table 3. The average
scores for the three criteria were 4.3, 3.3 and 4. No evident difference between the two surgeons was found.

5. Discussions

This paper presented an image-guided puncture for PCNL by augmenting the intraoperative US with a kidney model and a virtual needle. The kidney model was represented as a triangular surface mesh reconstructed using SSM and sparse points picked from the US images. The reconstruction method consists of an ICP registration and a statistical instantiation. A respiratory gating technique was used to guarantee the consistency of all selected US images at ME positions. The surgeons were allowed to reconstruct a kidney model in a fine-tune way. The accuracy and inter-operator repeatability of the reconstruction method were evaluated by two urologists on pig data. Comparative studies of the proposed and tradition PCNL in pig models were conducted to assess the feasibility and efficiency of the presented image-guided intervention method. Based on our analysis and experiment results, we have the following findings.

(1) The reconstruction accuracy depended on not only how many points were picked, but also how “well” the points were picked. According to our experience, a successful percutaneous PCS puncture requires the reconstruction error to be less than 2 mm. In our experiments, 30 points were enough to generate a kidney model with less than 2 mm RMS distance to its reference shape. Although in our experiments more input points yielded more accurate reconstruction, it is not always true. A counter example is shown in Fig. 10, where 100 points were picked. It can be observed that the ICP registration was incorrect, leading to a bad kidney model. The reason can be explained as follows. In our two-step reconstruction process, the second step, statistical instantiation, depends on the outcome of the first step, ICP registration. Well-selected sparse points could significantly improve the ICP registration and therefore yield an accurate reconstruction model. As mentioned in the third paragraph of Section 2.3, well-picked point set (1) should contain three initialization landmarks located on cranial pole, caudal pole and renal hilum center, (2) should be on distinct and recognizable kidney contours in the US images, and (3) should be distributed as evenly as possible over the kidney surface. Otherwise, the ICP registration...
will fail, which will produce an implausible kidney model. The bad reconstruction in Fig. 10 was due to inaccurate initialization landmarks. On the other hand, experiment results have shown that for a well-selected point set that generated the accurate kidney model, adding more points will not significantly increase the accuracy. Therefore, it is a reasonable assumption that there exists a tradeoff between the input point number and the final reconstruction accuracy.

To avoid inappropriate and unnecessary point-picking, we employed a fine-tune reconstruction method. After adding or removing each point, the kidney model can be quickly updated and displayed. Therefore, the surgeon can immediately check the visual quality of the updated kidney model after each point picking or removing. This feature allows surgeon to reconstruct an acceptable kidney model using as less points as possible and therefore reduces the operation time.

Fig. 7. Leave-one-out validation result: mean reconstruction error with standard deviation against different input point numbers. (a) Mean error for the left kidney. (b) Mean error for the right kidney. (c) Mean error difference for the left kidney. (d) Mean error difference for the right kidney.

Fig. 8. Mean reconstruction time against different input point numbers. (a) Computation time including SI (Statistical Instantiation) time and ICP registration time. (b) Point-picking time.
For different operators, the reconstruction method was repeatable as long as all operators were well trained. The inter-operator variation in the final result were induced in the point-picking stage. To minimize this inter-operator variation, the operators should be trained to select optimal points in US images, i.e. picking points in a fine-tune way according to the three principles mentioned above. In our study, both surgeons were familiar with the US image and image-guided renal intervention. Both of them were well trained to use the proposed methods in pigs before all experiments.

Large training population in SSM building was able to improve the reconstruction accuracy. In a previous report in [33], it was found that sometimes estimates with small population were better than those with large one. The authors supposed that large training population became biased against accurate prediction of certain shape. In our experiments, all tests using large population yielded better results than those using small one. We recommend to establish large-scale database to construct non-biased SSM.

The use of the proposed intervention improved the visual perception as well as the target location. To avoid large vessels and surrounding organs, the punctures were often performed though the 11th intercostal space between the posterior axillary line and scapula line into the posterior middle calix. In such a case, it is familiar with the US image and image-guided renal intervention. Both of them were well trained to use the proposed methods in pigs before all experiments.

![Fig. 9. Mean reconstruction error using a different training population against different input point numbers. (a) Mean error for the left kidney. (b) Mean error for the right kidney.](image)

**Table 1**

Left kidney reconstruction error for the 23rd–28th pigs in the PCNL experiment.

<table>
<thead>
<tr>
<th>Operator</th>
<th>Pig #</th>
<th>KL</th>
<th>HLZ</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>23</td>
<td>24</td>
<td>25</td>
</tr>
<tr>
<td>Input point number</td>
<td>67</td>
<td>89</td>
<td>72</td>
<td></td>
</tr>
<tr>
<td>Point-picking time (s)</td>
<td>267</td>
<td>259</td>
<td>232</td>
<td></td>
</tr>
<tr>
<td>RMS error (mm)</td>
<td>1.12</td>
<td>0.95</td>
<td>1.01</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2**

Comparison of the proposed and traditional PCNL in pigs.

<table>
<thead>
<tr>
<th>Pig #</th>
<th>Kidney</th>
<th>Time (min)</th>
<th>Access failure</th>
<th>Complications</th>
</tr>
</thead>
<tbody>
<tr>
<td>23</td>
<td>Left</td>
<td>14</td>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>11</td>
<td>1</td>
<td>Bleeding</td>
</tr>
<tr>
<td>24</td>
<td>Left</td>
<td>12</td>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>6</td>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td>25</td>
<td>Left</td>
<td>11</td>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>3</td>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td>26</td>
<td>Left</td>
<td>15</td>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>12</td>
<td>1</td>
<td>Bleeding, mild infection</td>
</tr>
<tr>
<td>27</td>
<td>Left</td>
<td>11</td>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>5</td>
<td>0</td>
<td>Bleeding</td>
</tr>
<tr>
<td>28</td>
<td>Left</td>
<td>8</td>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>4</td>
<td>0</td>
<td>–</td>
</tr>
</tbody>
</table>

**Table 3**

Subjective assessment of the proposed image guidance method.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Surgeon KL</th>
<th>Surgeon HLZ</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intv Imprv</td>
<td>4</td>
<td>4.5</td>
<td>4.3</td>
</tr>
<tr>
<td>Wdlo Impct</td>
<td>3.5</td>
<td>3</td>
<td>3.3</td>
</tr>
<tr>
<td>Cln Relvce</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

Fig. 10. An example of bad ICP registration (left) and the resulted kidney model (right) with 100 input points.
difficult in the US image to accurately locate the target and guarantee an optimal puncture trajectory, which could cause bleedings. On the other hand, the far-side kidney boundary against the US probe is often fuzzy. This may cause renal pelvis perforation. A worldwide study on PCNL with 5803 patients reported that the complication rate was 7.8% for bleeding and 3.4% for renal pelvis perforation [34]. Compared with traditional US-guided PCNL, additional information such as the kidney contours and a virtual needle was provided by our augmented guidance and superimposed onto the US images. These visualized models were designed for the purpose of quickly localizing the PCS and accurately puncturing into it. Moreover, the proposed technique provided a more intuitive guidance interface containing a 3D kidney and a tracked needle, as shown in Fig. 3. Therefore, we believe that the anatomy and spatial relations appeared more clearly and can be better comprehended.

A latest review study on kidney targeting and puncturing in PCNL reported that medical imaging guidance, motion tracking systems, image processing and computer graphics were the most relevant contributions [35]. It also implied that real-time methods, robust and accurate algorithms, and radiation free imaging techniques were promising in future PCNL techniques. The proposed guidance made use of recent image processing progresses on shape modeling and 3D visualization, in order to reduce the rate of complications during percutaneous puncture and lower the radiation injury. Compared with other techniques the advantages of our image guidance method include (1) Without CT or MR data, an patient-specific kidney surface can be obtained. (2) No complicated registration between multiple image modalities is required. (3) No expensive, large or heavy devices such as C-arm systems totally excluded in this study. Second, in this initial report, we guarantee accurate and repeatable reconstruction within acceptable time.

Our study has the following limitations. First, the number of pigs in our experiments was still small. Biased results cannot be totally excluded in this study. Second, in this initial report, we focused on assessing the feasibility and efficiency of our proposed image guidance tool in healthy pigs. No pathological cases were included, so the results obtained in this paper may be biased for pathological kidneys. Additionally, due to the limited number of animals in our study, we did not compare the case of augmenting animals in our study, we did not compare the case of augmenting the US with only an overlaid needle (without SSM model). Such a comparative study will provide a more comprehensive evaluation of the SSM-based navigation technique. Future studies will focus on how to further reduce human interaction and operation time in kidney model reconstruction.

6. Conclusion

Our experimental results have validated the feasibility and efficiency of the proposed augmented US-guided puncture for PCNL in healthy Wuzhishan pigs. With careful setup by trained surgeons, our proposed guidance has the potential to reduce the occurrence of complications such as PCS access failure and bleeding compared with a traditional US-guided method.

References

Zhi-Cheng Li received the B.S. degree in electronic information engineering and M.S. degrees in signal processing, both from Shandong University. He pursued the Ph.D. degree at Beijing University of Posts and Telecommunications. From 2007 to 2008, he worked in Nanyang Technological University, Singapore as a China-government sponsored scholar. Currently, he is an associate professor with Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, where he investigates novel approaches to image-guided. His research interests include medical image processing, image-guided therapy and traditional Chinese culture.

Kai Li is an associate chief physician in the department of medical ultrasonics at the third affiliated hospital of Sun Yat-Sen University. He has focused his work on interventional ultrasound since 2004, especially in the field of ultrasound-guided renal intervention, hepatocellular carcinoma ablation and medical image fusion. He is also a lecture in the Sun Yat-Sen University. He has published a number of research papers and filed 2 international patents.

Hai-Lun Zhan is an associate chief physician in the department of urology at the third affiliated hospital of Sun Yat-Sen University. He is a high volume surgeon performing over 100 interventional urological surgery per year. His specialties include renal stones surgery, renal cell carcinoma surgery and the surgical techniques of endourology. He is also a lecture in the Sun Yat-Sen University and has published a number of research papers.

Ken Chen received his bachelor degree in Beihang University in 2008, and got his master degree in 2010, both in Electrical Engineering. From 2010, he has been working in Shenzhen Institutes of Advance Technology, Chinese Academy of Sciences as an Engineer. His research interests lie in medical image analysis and image-guided intervention.

Yao-Qin Xie received his B.Eng., M.Eng., and Ph.D. from Tsinghua University of China in 1995, 1998, and 2002, respectively. He is working in Peking University of China from 2002, and joined Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, on 2010. He joined Stanford University as a postdoctoral fellow from 2006 to 2008. He has published more than 100 papers. He is a member of American Association of Physicist in Medicine (AAPM), a referee of Medical Image Analysis, Physics in Medicine and Biology, IEEE Transactions on Biomedical Engineering, IEEE Transactions on Information Technology in BioMedicine.

Lei Wang received his B.Eng. in Information and Control Engineering and Ph.D. in Biomedical Engineering, in 1995 and 2000, respectively, from Xi’an Jiaotong University, China. He was with University of Glasgow and Imperial College London during 2000–2008. He is now with the Shenzhen Institutes of Advanced Technology (SIAT), Chinese Academy of Sciences, as a full professor. He is the director of the center for medical robotics and minimally invasive devices in SIAT. His research interests are Body Sensor Networks and Biomedical IC design. He has published more than 200 scientific papers, authored four book chapters and filed 60 patents.

Ming-Min Chen received M.S. degree in Computer Science from University of Birmingham, UK, in 2010. From October 2012, he is a Research Assistant in Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. His research interests include medical image processing and parallel computing.