Automatic tomographic ultrasound imaging sequence extraction of the anal sphincter

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Abstract. Transperineal volumetric ultrasound (TPUS) imaging has become routine practice for diagnosing anorectal dysfunction, a life-challenging pelvic floor dysfunction (PFD). To assess the integrity of the whole length of the anal sphincter from three-dimensional (3D) ultrasound (US) data, sonographers first extract a tomographic US imaging (TUI) sequence from the TPUS recording. TUI sequences consist of eight equally spaced and properly oriented two-dimensional (2D) coronal-view slices of the anal sphincter complex. TUI sequences are visually assessed by a sonographer to diagnose anal sphincter injury. Obtaining TUI sequences is performed manually in clinical practice, which is labour-intensive and requires expert knowledge of pelvic floor anatomy. To the best of our knowledge, this work is the first to report an automatic method to aid this medical imaging acquisition task. We propose a novel, convolutional neural network (CNN) approach for the automatic extraction of the TUI sequences from a TPUS. The method utilises a CNN to segment the external anal sphincter (EAS), and the desired TUI sequences are subsequently extracted after several automatic post-processing steps. The proposed method is evaluated on 30 TPUS recordings and compared against manually acquired gold standard TUI sequences. One expert evaluated the quality of the automatically detected TUI sequences in terms of their clinical acceptability for diagnosis. The automatic method performs with an overall clinical acceptability of 90.00%. The method reduces the time required to extract the anal sphincter complex TUI sequence of a TPUS by 52.36 seconds and may reduce the need for high-level expertise in anorectal dysfunction analysis.

1 Introduction

PFD includes pelvic organ prolapse, urinary incontinence and anorectal dysfunction, including anal incontinence and obstructive defecation. Obstetric anal sphincter injury is the most common finding in women with anal incontinence in reproductive age. Anal sphincter integrity (or injury) can be assessed with exo-anal (TPUS or introital) or with endo-anal US. Endo-anal is more intrusive, and TPUS showed a substantial correlation with exo-anal with high sensitivity for anal sphincter complex evaluation [6]. TPUS has shown to have similar image quality to introital with lower inter-rater variability [10, 6, 2]. Therefore, TPUS was used in this study, further details can be found in literature [6, 2, 3].

Within clinical assessment, sonographers use TUI sequences of the anal sphincter complex to visually assess the integrity of the entire anal sphincter [7, 3]. TUI sequences consist of eight equally spaced and properly oriented 2D coronal view slices of the anal sphincter complex. Manual extraction of TUI sequences from a TPUS recording is labour intensive and recognised as a highly skilled task, as the sonographer must manually manipulate a TPUS recording to locate predetermined locations, based on the cranial termination of the EAS and the caudal termination of the internal anal sphincter (IAS) [6, 2, 3], as shown in Fig. 1. The quality of TUI extraction is heavily dependent on the sonographer's skill, and significant inter-observer variability may lead to, in extreme cases, misdiagnosis.

Therefore, we aim to automatically extract the TUI sequences from a TPUS recording, to address the limitations above. In this work, the sonographer would only need to acquire a TPUS recording following a standard acquisition, (i.e. the transperineal probe is placed at the opening to the vagina and perpendicularly to the anal canal) [6]. Our solution aims to speed up assessment for skilled sonographers, and potentially allow non-experts to perform these assessments.

We briefly describe our work in the context of related literature that has proposed automated image analysis of pelvic floor structures, such as the levator hiatus [1, 5, 9] and the puborectalis muscle [11]. Automatic assessment of the levator hiatus [1, 5] utilised CNNs and active shape models [9], and performed within inter-observer variability. In other work, an automatic clinical solution was presented for the extraction of a plane of interest used in PFD assessment[12]. The paper utilised CNN landmark regression, and performed within inter-observer variability, while reducing the time required for assessment by 100 seconds.

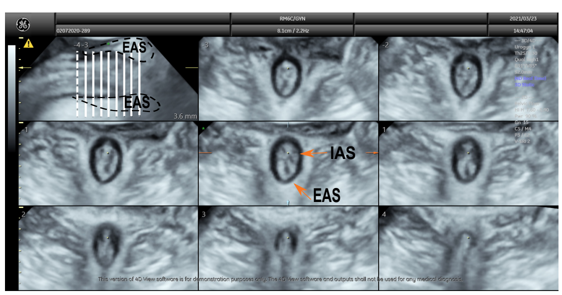

Fig. 1. TUI sequence of a normal anal sphincter. The top left image shows the midsagittal plane with the EAS annotated; the eight other images represent coronal slices through the anal canal. The locations of the slices are given by the vertical lines in the midsagittal plane. Slice 1 is the non-dashed vertical line on the left; slice 8 is at the right. The arrows show the location of the EAS and IAS within a coronal view plane.

We believe the work presented in this paper is of clinical impact, due to the difficult nature of manipulating TPUS recordings of the anal sphincter, the lack of current automation of TUI extraction, and the expertise required by sonographers. In this paper, we describe to the authors' knowledge the first automatic anal sphincter TUI sequence extraction solution. The proposed solution locates the EAS and extracts eight equidistant 2D images of the anal sphincter in the coronal-view, comparable to manually acquired TUI sequences. This work utilises the advances of CNN segmentation and is evaluated on 30 TPUS recordings. The clinical acceptability and time taken are recorded and compared to an expert sonographer. We believe a fully automatic TUI extraction solution may save clinicians time to allow more focus on patient care and treatment planning.

2 Materials and methods

During urogynaecological US examination, sonographers aim to evaluate sphincter integrity based on the sonographic appearance of the EAS and IAS. The sonographer acquires a TPUS recording at approximately 60 deg aperture and 70 deg acquisition angle with a 3D convex transducer, when possible during pelvic floor muscle contraction. The TUI sequences are identified in post-processing steps. On the extracted TUI sequences, the sonographer assessed EAS and IAS integrity, and if present measured the degree of tear in the EAS and in the IAS which corresponds to the internationally accepted clinical classification [3]. Before describing the method in detail, we first describe the acquisition protocol.

2.1 Acquisition protocol

All data was acquired with a Voluson E10 BT16 ultrasound system (GE Healthcare: Zipf, Austria) equipped with a 3D 4-8 MHz convex probe placed transperineally with an average voxel resolution of 0.3 mm by 0.3 mm by 0.3 mm. For testing, a total 30 3D TPUS recordings were acquired. Volumes covering the entire length of the EAS were obtained and post-processed offline on a desktop computer using 4D View Software (GE Healthcare; Austria GmbH & Co, Zipf, Austria) according to the international practice parameter [8].

2.2 The proposed pipeline

The proposed method is shown in Fig. 2. Firstly, the EAS was segmented from a TPUS recording, the centre of mass, X_{cm}, was determined and the corresponding mid-sagittal plane extracted. Four parallel planes were extracted and an averaged EAS segmentation was formed. The principal axes of rotation of the averaged segmentation was identified and a rotation matrix was formed. The TPUS was then rotated to ensure the anal sphincter was parallel to the coordinate axes, and eight equidistant slices of the EAS in the coronal view were extracted.

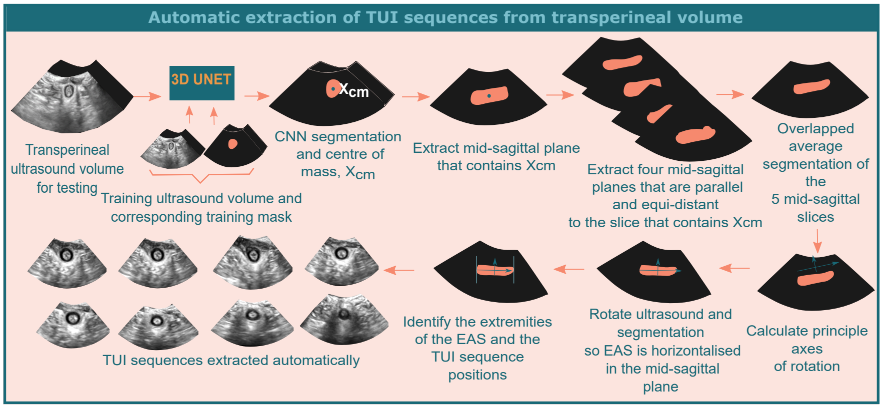

Fig. 2. Proposed pipeline of the automatic TUI extraction algorithm

3D EAS segmentation Firstly the EAS was automatically segmented. This was achieved by utilising a CNN, which accepted a TPUS as input and outputted a 3D voxel-wise segmentation of the EAS. The architecture used was 3D U-Net [14], and advanced data augmentation was used including an adaptation of the original mix-up [13], where three images and their labels were linearly combined.

Rotation of the TPUS recording During manual acquisition the sonographer may need to rotate the TPUS to horizontalise the anal canal in the mid-sagittal plane. This ensures the axes of rotation of the sphincter lay along the coordinate axes. Here, we describe how the rotation matrix, R, was formed in order to automate this task. Firstly, X_{cm} of the 3D segmentation was identified, and the mid-sagittal plane of the segmentation which contained X_{cm} was extracted. The mid-sagittal plane is given by the x and y directions of the volume data, and is dependent on a standard acquisition protocol used within clinic (i.e. the probe placed at the entrance of the vagina perpendicular to the anal canal). Several equidistant parallel planes to the mid-sagittal plane containing, X_{cm} were extracted and multiplied together to produce an averaged 2D EAS segmentation, based on the common overlap (i.e. common voxel values were equal to 1 and uncommon voxel values were equal to 0).The mid-sagittal planes used contained the coordinate X_{cm}, $X_{cm} \pm 1.5mm$ and $X_{cm} \pm 3mm$.

Principle component analysis (PCA) was used to identify the eigenvectors, $\vec{v}_{av}$, describing the principle axes of rotation of the averaged 2D EAS segmentation within the mid-sagittal view. PCA was only applied to the mid-sagittal view rather than the total 3D segmentation, to follow aspects of the clinical procedure. PCA was applied to the averaged 2D EAS segmentation, rather than the mid-sagittal plane containing X_{cm} to make the method more robust, and reduce the risk of incorrect rotation due to poor segmentation of the EAS within one mid-sagittal plane. To form the rotation matrix, R, the inverse of the averaged eigenvector, $\vec{v}_{av}^{-1}$ was computed. The rotation matrix, R, was defined as:

$$R = \|R_x\| \, \|R_y\| \, \|R_z\| = \begin{Vmatrix} 1 & 0 & 0 \\ 0 & \vec{v}_{av_{xx}}^{-1} & \vec{v}_{av_{yx}}^{-1} \\ 0 & \vec{v}_{av_{xy}}^{-1} & \vec{v}_{av_{yy}}^{-1} \end{Vmatrix}. \quad (1)$$

Where $\vec{v}_{av_{xx}}^{-1}$ and $\vec{v}_{av_{xy}}^{-1}$ define the x and y component respectively of the eigenvector along the length of the anal canal, and $\vec{v}_{av_{yx}}^{-1}$ and $\vec{v}_{av_{yy}}^{-1}$ define the x and y component respectively of the eigenvector along the width of the anal canal. The TPUS and CNN segmentation were rotated in preparation for TUI extraction.

Unfortunately, occasionally the rotation angle determined as above may be too severe, due to a non cylindrical EAS segmentation. Therefore, before TUI extraction occurred an automated quality control process was performed. The ratio between the largest and smallest eigenvector component was calculated, and when the ratio was smaller than a pre-defined threshold, the rotation matrix was set to identity, and the TPUS and segmentation were not rotated. The pre-defined threshold was 2.11 and it was determined in preliminary studies, based on the relationship between the eigenvector component ratio and the rotational acceptability score. In detail, a sample of 10 incorrectly rotated TPUS recordings were used, the mean ratio and standard deviation were calculated, and the threshold was set to the upper bound of the 95% confidence limit.

Identification of extreme points To extract TUI sequences, the extreme points as shown in Fig. 2 were identified. X_{cm} of the rotated CNN segmentation was calculated and the rotated mid-sagittal plane containing X_{cm} was extracted. After rotation the major axes of the EAS were parallel to the coordinate axes, and the first and last coordinate along the y axis of the EAS segmentation were extracted. The total length of the EAS was calculated and divided by 9 to determine the slice separation (i.e. distance between 2D slices in coronal-view of the anal sphincter complex), thus 8 slices were extracted excluding the first and last coordinate position of the EAS. This reduced the risk of selecting a plane too far from the optimal position due to poor segmentation. During examination the spacing between TUI sequences should be larger than 2mm, thus a quality check was performed prior to extraction, and when the slice separation was smaller than 2mm the total length of the EAS was divided by 7 and the TUI sequences included the extremities of the EAS segmentation. If the slice separation was still smaller than 2mm the algorithm outputted the TUI sequences and a notification that the length of the detected EAS may be insufficient or abnormal.

2.3 Data collection

Analysis of anonymised, archived US images was retrospective, so ethics committee approval was not required by Belgian law. The TPUS recordings were acquired at the pelvic floor clinic at UZ Leuven, Belgium between February and November 2020. The data was separated into training and test sets such that each patient was in one set only. In total 148 3D TPUS recordings were used; 94 for training, 24 for validation and 30 for testing. An expert sonographer with over four years' of experience in US PFD assessment, manually extracted TUI sequences of the anal sphincter for clinical diagnosis using 4D View software (GE Healthcare, Zipf, Austria). The same expert manually segmented the EAS complex with rotations of 30 *deg*, using the volume analysis application VOCAL from 4D View Software (GE Healthcare, Zipf, Austria) from the 3D TPUS recordings, these were used as ground truth labels for training.

2.4 Evaluation methodology

The expert identified the TUI sequences in all TPUS recordings manually via the clinical protocol using 4D View software (GE Healthcare; Zipf, Austria). These TUI sequences are defined as gold standard and were visually compared to the automatically detected TUI sequences. To assess the performance of the proposed method, the expert was asked to rate the overall performance of the automatically detected TUI sequences for each TPUS volume: visually "clinically acceptable" or "unacceptable" for clinical diagnosis. They were also asked to rate the rotation of the anal canal within the mid-sagittal plane and the quality of each TUI slice as either "clinically acceptable" or "unacceptable". The slice rating was dependent on the automatic slice being visually similar to the gold standard and of use for clinical diagnosis (i.e. showing the same pathology if present). The time taken for the automatic pipeline to identify the TUI sequences was compared to the time taken by the expert to manually extract the TUI sequence on a new subset of 19 TPUS recordings acquired within clinic, via the clinical protocol using 4D View software (GE Healthcare; Zipf, Austria). In addition the slice separation of TUI sequences determined automatically and manually were compared.

3 Experiments, Results and Discussion

3.1 Implementation details

The proposed tool was implemented on a Windows desktop with a 24GB NVIDIA Quadro P6000 (NVIDIA, California, United States). The CNN was implemented using NiftyNet [4], training and inference were ran on the GPU. The CNN architecture was 3D U-Net [14], an Adam optimiser, ReLU activation function, weighted decay factor of 10^{-5}, Dice loss function with a learning rate of 0.0001 and batch size of 2 were used. The data augmentation used were: elastic deformation (deformation sigma = 5, number of control points = 4), random scaling (-20%,+20%) and an implementation of mixup [13]. Validation of the CNN training was performed every 200 epochs and it trained for 6000 epochs. The model from epoch 3200 was used at inference, as the validation loss function was lowest.

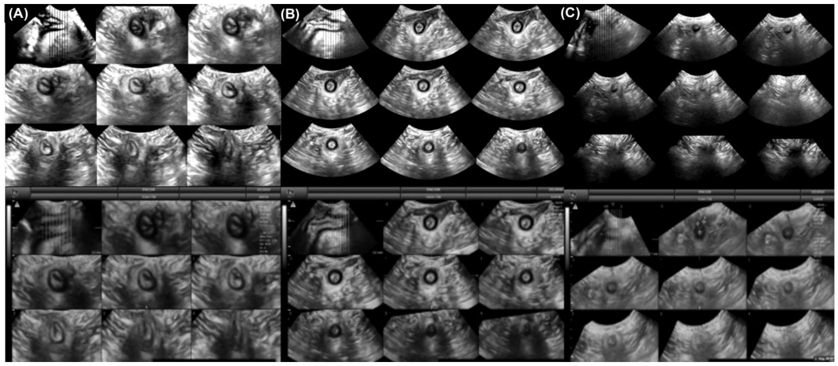

Fig. 3. TUI extraction results, a) the best performing result, b) the average performing result and c) the worst performing result. The corresponding gold-standard TUI sequence for each result are shown in the second row.

Table 1. Overall and rotational clinical acceptability, time taken and slice separation.

Method	Overall clinical acceptability, %	Rotation clinical acceptability, %	Time s	Slice separation mm
Automatic method	90.00	93.33	8.64± 0.17	2.84± 0.50
Manual	100	100	61.00±13.74	2.81 ± 0.37

3.2 Results

Qualitative results of the automatically extracted TUI sequences compared to the gold standard are shown in Fig. 3. Fig. 3c shows the worst performing result (based on overall, slice and rotational acceptability), Fig. 3b the average performing result, and Fig. 3a the best performing result. The overall clinical acceptability, the rotation performance, the time taken, and the average slice separation are shown in Table 1. Table 2 shows the clinical acceptability scores of the automatic method for each TUI slice.

3.3 Discussion

The study presents to the-authors-knowledge the first automatic TUI sequence extraction pipeline from a TPUS recording. Qualitatively in Fig. 3 there is minimal visual difference between the automatically and manually extracted TUI sequences for the average and best performing result and they both show the same clinical diagnosis. The worst-performing result was clinically unacceptable

Table 2. Slice number and corresponding clinical acceptability.

Slice number	1	2	3	4	5	6	7	8
Clinical acceptability	70.00	86.67	90.00	93.33	96.67	96.67	96.67	90.00

for all slices, due to the incorrect rotation and location of the TUI sequence. Incorrect rotation was due a non cylindrical EAS with a ratio of 3.45, which was larger than the pre-defined threshold. Incorrect rotation meant the TUI sequences did not intersect the anal canal perpendicularly, and incorrect location of the first TUI sequence resulted in sequences that were not clinically suitable. The average-performing result had a rotation that was clinically acceptable, however, the position of the final slice was not optimal as it contained part of the IAS unlike the gold standard. This does not impact the overall clinical acceptability as the same diagnosis was made. The best performing result, was rated as clinically acceptable for all slices and for the rotation. The visual difference between the automatic result and the gold standard is negligible and any differences are due to the post-processing of 4D View (GE Healthcare; Zipf, Austria).

The proposed method was 52.36 seconds faster than the clinical expert, which was significant ($p < 0.001$), and the variance of time taken decreased significantly ($p < 0.001$). The average slice separation of the proposed method was not statistically higher than the manually acquired slice separation ($p = 0.265$). The overall clinical acceptability of the proposed method was 90.00%, on average 7.16 TUI sequences out of 8 were marked as clinically acceptable and the rotation scored a clinical acceptability of 93.33%. 11 TPUS volumes were not rotated as the quality control process detected a ratio of eigenvector components smaller than or equal to 2.11. Slice 1 and 8 describe the extremities of the EAS, and are the most dependent on the segmentation. Table 2 shows slice 1 and 2 were the least clinically accurate, the location of the first slice may improve with a larger training dataset of EAS segmentations. The other slices performed similarly.

The strengths of this work are that it allows a non expert to extract the TUI sequences for diagnosis, and it saves a significant amount of time for all (expert and non-expert) sonographers. Automation may standardise the current procedure and reduce inter-observer variability, this will be studied in future work, on a larger dataset. The main limitation, is the formation of the rotation matrix, as it is dependent on the EAS segmentation. Incorrect segmentation due to artefacts, may lead to a non-cylindrical shape, and the volume may not be rotated at all, or rotated too much. In some patients biologically the EAS may not be cylindrical during contraction, regardless of CNN performance. Thus, in the future, we aim to include segmentation information of the IAS. In addition, to follow clinical guidelines more closely, we aim to ensure the anal canal is not only horizontally aligned in the mid-sagittal plane, but also that it is vertically aligned in the axial plane. This would improve results when the US is acquired sub-optimally (i.e. asymmetric), allowing less-skilled sonographers to perform TUI extraction. As the current method does not correct asymmetric US recordings in the axial plane, the TUI sequences may not intersect the anal canal perpendicularly, leading to sub-optimal TUI sequences. Previous work highlighted that inter observer agreement for sphincteric measurements was fair to excellent for transperineal acquisition [2], however, in future work the evaluation will be expanded to several clinical observers to calculate intra and inter observer variability to reduce bias. Furthermore, the pipeline will be extended to classify anal sphincter tears and disease if present.

4 Conclusion

To conclude, the proposed method achieved an overall clinical acceptability of 90.00%, despite the limitation of the rotation matrix and not rotating the axial plane as performed in clinic to improve asymmetric acquisitions. Thus, we believe with a more detailed pipeline which includes IAS segmentation, the results will outperform this method, and may perform comparable to inter-observer variability. The proposed method was 52.36 seconds quicker than the clinical expert, which was significant. The proposed method allows non-expert sonographers to perform TUI sequence extraction for anal sphincter tear diagnosis. In future work we will conduct an inter and intra observer variability study, and expand the evaluation dataset to 100 TPUS volumes.

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