RE: Response to Peer Review Comments

We would like to thank the Associate Editor and the anonymous reviewers for their careful consideration and the time taken to both read and criticize the submitted manuscript, TII-15-1026, with the title “Computer-assisted 3D Ultrasound Probe Placement for Emergency Healthcare Applications”. Your constructive comments are well-received and highly appreciated. The manuscript is revised to address the Associate Editor and reviewers’ comments, and we hope that the revised manuscript meets the standards and requirements of the IEEE Transaction on Industrial Informatics. Summarized changes in the revised manuscript are listed as follows,

- adding experimental results on the Euclidean distance error of detected kidney’s center points,
- representing statistical variation using box-plot of the Euclidean distance errors of the proposed method and the state-of-the-art,
- adding data analysis based on Wilcoxon rank-sum test on the reported Euclidean distance errors,
- adding computational time analysis of the proposed solution.

The reviewers’ comments are highlighted in **bold/italicized font** with the authors’ answers provided in regular font. For ease of reference, pertinent sections of the revised manuscript are reproduced in this document in *italic size 9pt font*. All references and discussions included in this document correspond to pertinent sections of the double column version of the revised manuscript. References to the revised manuscript are noted by page number, section number, column number, paragraph, equation or line numbers as it may be required. The introduced changes to the revised manuscript in this document are highlighted in the revised manuscript using **blue-colored normal font**.

Lastly, the authors would like to thank the Editor-in-Chief and Associate Editor for the time taken to communicate materials to the authors and for coordinating the review process.
I. ASSOCIATE EDITOR COMMENTS

(AEC.1) This paper introduced a new solution to provide computer-assisted ultrasound probe placement for imaging abdominal organs without obtaining help from a remote expert. The subject of this investigation is of great interests. Comparison of the proposed kidney detection method with other methods are done (table 1). It would be more informative if more data analysis on the developed method on key parameters (such as accuracy, sensitivity and specificity) can be given to fit into the scope of TII. The authors may study papers published in TII (and possibly quote the right papers, at the moment NONE) for such an analysis. Minor revision is needed.

Answer to (AEC.1): First of all, the authors would like to thank the Associate Editor for the positive feedback on the proposed solution of the submitted manuscript, TII-15-1026. The Associate Editor’s point on adding data analysis is well taken. First of all, the authors want to emphasize the point that the accuracy, sensitivity, and specificity measures are applied on the number of true and false detections in the with-kidney and without-kidney images of the evaluation set, and these measures are not calculated for each individual image samples. Therefore, data analysis of the reported accuracy, sensitivity, and specificity measures could not be applied to show the significance of the obtained results using the proposed method in this paper, compared to the other methods.

In order to perform data analysis, we have added new experimental results in the revised manuscript, reporting the Euclidean distance error (pixels) of detected center points of the kidney’s shape in the with-kidney ultrasound images for the proposed method of this paper, Marsousi-EMBC14 [7], and Noll14 [16]. The new measure, the Euclidean distance error, is calculated for each with-kidney image per each method, and therefore, this error-measure is applicable to perform a useful data analysis to investigate the significance of the reported results of this paper. Please note that in the calculations of detection accuracy, sensitivity, and specificity, we only concern whether the detected center points are placed within an acceptable distance from the actual center points. However, these measures do not reflect the accuracy of detected center points, with respect to the actual center point of the organ’s shape. Hence, the recently added experimental result of Euclidean distance error is not redundant with the previously reported results. The Euclidean distance error, “d”, has been defined in the revised manuscript, in Page 7, Sec III.D, 1st column, Paragraph 3, line numbers 36 to 42, as follows,

\[ A \text{ true positive (TP) detection refers to a RCC outcome of a with-kidney image that } \Gamma^* > \Gamma^{th} \text{ and } d = \| \vec{X}^* - \vec{X}^{ac} \|_2 < d_{max} \]

where \( \vec{X}^* \), \( \vec{X}^{ac} \), \( d \), and \( d_{max} \) are the detected organ's shape center, actual organ's shape mass center, the Euclidean distance
error of the detected and actual organ’s centers, and maximum acceptable Euclidean distance error, respectively.

In the revised manuscript, we have used the box-plot representation to visually report the statistical variation of the calculated Euclidean distance errors. The box-plot graph is known to be an effective way to visually represent statistical parameters, such as mean, standard deviation, minimum, maximum, and median of data samples, and it has been widely used in related IEEE transactions to the topic of this paper, particularly in the IEEE transaction on Industrial Informatics (TII). The reason of using the box-plot representation is explained in the revised manuscript by quoting two journal papers, published in the IEEE-TII, as follows:


The new box-plot has been added in the revised manuscript as Fig. 8. According to the box-plot of Fig. 8, the proposed method offers smaller average and standard deviation of the Euclidean distance error, compared to Marsousi-EMBC14 [7], and Noll14 [16]. For the ease of referencing, Figure 8 is copied here,

![Box-Plot Graph](image-url)

Fig. 8. Displaying the box-plot graph of Euclidean distance errors (pixels) of the detected center points of the kidney shape in the *with-kidney* images of the healthy volunteers.

To better fit into the scope of the IEEE-TII, we have added two data analysis in the revised manuscript, based on investigating binary hypothesis, to validate that the reported results of the Euclidean distance
error of this paper is significantly better than the other methods. (By searching among IEEE-TII published
papers, we have found many journal papers, reporting binary hypotheses as a data analysis tool to prove
the significance of their reported results.) Since, the number of samples in the evaluation set of this paper
is small, and the samples are not normally distributed, we applied the Wilcoxon rank-sum test to perform
data analysis. This is explained in the revised manuscript by quoting the following IEEE-TII journal
paper,

[38] M.-D. Ma, D. S.-H. Wong, S.-S. Jang, and S.-T. Tseng, Fault detection based on statistical

In the revised manuscript, we have defined two null hypotheses that (1) the result of the proposed
method in this paper is not significantly better than the Noll14 method, and (2) the result of the proposed
method in this paper is not significantly better than the Marsousi-EMBC14 method. The resultant values
of p-value for the two null hypotheses, calculated by the Wilcoxon rank-sum test, are $p = 0.0035$ and
$p = 0.0010$ at the 5% significance level, which reject the null hypotheses, and indicate that the detected
center point results of the proposed method of this paper is significantly better than Marsousi-EMBC14
and Noll14 methods.

The new experimental result and the performed data analysis have been added in the revised manuscript
in page 8, Sec III.E, 1st column, paragraph 2, line number 32 to 2nd column, paragraph 1, line number
3. For the ease of referencing, its copy is provided here:

For further validation, the Euclidean distance errors of the detected center points, with respect to the actual center points,
of the kidney shape in the with-kidney images of the healthy volunteers are compared for the three methods. We used the
box-plot graph, displaying standard deviation, minimum, maximum, and outlier samples [36], [37], to visually represent the
statistical variations of the obtained results, as shown in Fig. 8. The mean and standard deviation of the Euclidean distance
errors of the proposed method, Marsousi-EMBC14 [7], and Noll14 [16] are $18.8052 \pm 16.3582$ px, $33.6812 \pm 18.9547$ px,
and $31.3152 \pm 12.5904$ px, respectively. Accordingly, the proposed method shows smaller average and median of the Euclidean
distance error of the detected center points. We also perform two data analysis to show the detected center point results obtained
by the proposed method is significantly better than the other methods. Because the number of samples (measured distance errors
in the with-kidney images) is small, and the samples are not normally distributed, the Wilcoxon rank-sum test is used instead
of the t-test [38]. In the first analysis, we defined a null hypothesis, $H_0$, that the results of the detected center points with the
proposed method of this paper is not significantly better than the results obtained by the Noll14 method [16]. The calculated
p-value, using the Wilcoxon rank-sum test, is $p = 0.0035$ at the 5% significance level, which rejects the null hypothesis, $H_0$. In
the second analysis, we defined a null hypothesis, \( H_0 \), that the results of the detected center points with the proposed method of this paper is not significantly better than the results obtained by the Marsousi-EMBC14 method [7]. The calculated p-value, using the Wilcoxon rank-sum test, is \( p = 0.0010 \) at the 5\% significance level, which rejects the null hypothesis, \( H_0 \). The two performed data analysis indicate that the proposed method of this paper provides smaller distance errors of detecting the center points of the kidney shape in 3D ultrasound images, compared to the other methods.

In addition, a new paragraph has been added in the revised manuscript to discuss the reported results and data analysis on the Euclidean distance errors of the detected center points, in Page 11, 1st column, paragraph 3, line numbers 37 to 52. For the ease of referencing, the pertinent material is copied here,

In the calculations of detection accuracy, sensitivity, and specificity, we only consider the detected center points are placed within an acceptable distance from the actual center points, however, these measures do not reflect the accuracy of detecting the center points, with respect to the actual center points. We calculated the Euclidean distance error of detected center points, with respect to their corresponding actual center points, of the kidney shape in the with-kidney 3D ultrasound images, as another key parameter to evaluate and compare the performance of the proposed method of this paper against the other methods. The reported results of the Euclidean distance errors of the methods and the performed statistical analysis indicate that the proposed method of this paper significantly performs better compared to the other methods, in terms of the accuracy of detecting center points of the kidney shape in 3D ultrasound images.

For the sake of clarity, we decided to explain the reason of using both with-kidney and without-kidney in the revised manuscript. The explanation has been added in page 8, Sec III.C, 1st column, paragraph 1, line numbers 5 to 7, as follows,

The use of both without-kidney and with-kidney allows us to evaluate the accuracy of detecting the kidney shape using the proposed method of this paper, compared to the other methods.
II. REVIEWER 1 COMMENTS

(REV1) The manuscript proposed a computer-assisted probe placement method for 3D medical ultrasound applications. The recent advances in algorithm and hardware implementation has paved the road for automated 3D ultrasound imaging devices, thus the subject of this manuscript is of great interests.

Answer to (REV1): The authors would like to appreciate the positive feedback of the first reviewer.

(REV1.1) The ultimate goal for the proposed method is to yield efficient and accurate diagnosis, but the manuscript lacks the experiments and results that can directly prove the systems efficiency. Here is one possible way to fix it: The authors may acquire several ultrasound images on different subjects using the proposed system, and ask a skilled technician to acquire a same set of images. Then invite a physician to score the image acquisition quality of each image without informing the image acquisition method. If possible, this should be repeated with several physicians and/or for different types of target organs.

Answer to (REV1.1): The authors would like to thank the reviewer for the insightful comment. However, they would like to bring to the reviewer’s attention the following very important points,

1) The proposed solution is an experimental device, currently at early prototype stage, without clearance for use in medical trials.

2) Given the nature of the device development, only a limited number of actual 3D ultrasound images are available to emulate real trauma diagnosis scenarios. This is to be expected given the experimental nature of the system.

3) The proposed “testing and verification” scenario recommended by the reviewer is most appropriate to be used with existing mature technologies, cleared due to their lengthy trial methods for medical use.

In the view of the authors, the use of simulated 3D ultrasound images in addition to the use of 3D ultrasound data sets reported in the manuscript provide enough data to verify, as per usual practice, the utility of the proposed method. It is the author’s thesis that the utility of the proposed experimental system can be sufficiently demonstrated by these experimental results.
(REV1.2) Since the image acquisition quality of the proposed system greatly relies on the realtime interaction between a paramedic and a portable device, a good question is whether the computational complexity of the proposed method can fit into a portable device with tight power budget. As a result, the manuscript has to include computational complexity analysis, and comparison with existing methods, or at least it should include the computation time or delay of the proposed method on the proposed computation platform, and why the authors are convinced that the proposed method will work on a portable device in the future.

Answer to (REV1.2): The reviewer's point is well taken. First, in the revised manuscript, we have emphasized the important point that the success of the proposed solution greatly relies on the computational time of the proposed solution to provide real-time interaction between operators (i.e. paramedics) and the diagnosis device in emergency healthcare, as follows,

- Page 11, Sec IV, 2nd column, paragraph 2, line numbers 11 to 13, as follows,
  
  The computational time of the proposed method has a vital importance for the proposed solution to be successfully applied in emergency healthcare.

- Page 10, Sec III.G, 1nd column, paragraph 2, line numbers 11 to 13, as follows,
  
  The success of the proposed system highly relies on the real-time interaction between an operator (i.e. paramedic) and the portable solution.

- Page 7, Sec II.D, 1nd column, paragraph 2, line numbers 5 to 9, as follows,
  
  The proposed organ detection method has a massive computational load, and the computational time should be minimized to be applicable in real-time interaction with a paramedic for triaging.

Secondly, we want to note this importance that the proposed solution of this paper is under-development stage, and MATLAB has been selected as the programming environment because it facilitates fast implementation and evaluation of the concept ideas. However, MATLAB is a high-level programming language, based on interpreting code-lines, which inserts a massive computational load on the proposed system. This point has been explained in the revised manuscript as follows,

- Page 7, Sec III, 2nd column, paragraph 1, line numbers 6 to 9 as follows,
  
  Since the proposed 3D ultrasound probe placement of this paper is currently under development-experimental stage, MATLAB has been selected as a well-suited environment to develop the concept idea, to implement the mathematical formulation, and to perform experimental analysis.

- Page 11, Sec IV, 2nd column, paragraph 2, line numbers 13 to 19,
  
  Since the proposed solution is underdevelopment, it has been developed in MATLAB, which simplifies and accelerates the
entire process of assessing a concept idea from its design through its evaluation. However, the overhead computational load might de-emphasize the utility of the proposed solution in the real-time interaction with an operator.

To minimize the overhead computational load of MATLAB, the following tricks have been applied: 1) avoiding the use of nested loops, 2) using built-in MATLAB functions, 3) utilizing GPU-powered MATLAB functions to perform highly parallelizable/non-complicated computations, and 4) using multi-threading multi-core capability of MATLAB to speed up complicated computations (i.e. the proposed registration method). The use of these tricks have been mentioned in the revised manuscript in Page 11, Sec IV, 2nd Column, Paragraph 2, line numbers 21 to 26. In addition, more explanation and details on the implementation methods to accelerate the proposed solution have been provided in the revised manuscript in Page 7, Sec II.D, 2nd column, paragraph 2, line numbers 6 to 26. Also, a new table, Table I, has been added in the revised manuscript to show how the parts of the proposed solution have been implemented. For the ease of referencing, the pertinent material is reproduced here,

The proposed organ detection method has a massive computational load, and the computational time should be minimized to be applicable in real-time interaction with a paramedic for triaging. The total computational time of the proposed organ detection is the summation of the computational times of the following parts: 1) noise reduction with Gaussian-Rectangular FIR filters, 2) local histogram equalization, 3) global and local thresholding, 4) rigid registration of the organ shape model, and 5) calculating the probe misalignment. The computational time of calculating the probe misalignment is very small, and therefore, it is not included in the analysis. Table I shows three types of the applied implementation methods to develop the parts in MATLAB R2015b, including the single-core sequential programming “Single-thread”, multi-threaded programming with multicore “parfor”, and GPU accelerated parallel programming “gpuArray”. For accelerating the preprocessing task, GPU programming is adopted to accelerate FIR filtering and local histogram equalization. For accelerating the registration process, each iteration is split into 12 threads, and each thread is dedicated for a single updating vector. Thus, the computational time of registration is reduced by \( \frac{1}{12} \).

Table I. Implementation methods of the parts of the proposed solution in MATLAB.

<table>
<thead>
<tr>
<th></th>
<th>Single-thread</th>
<th>parfor</th>
<th>gpuArray</th>
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</thead>
<tbody>
<tr>
<td>Speckle Reduction</td>
<td></td>
<td>✓</td>
<td></td>
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<tr>
<td>Local Histogram Equalization</td>
<td></td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Global and Local Thresholding</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Registration</td>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

In the revised manuscript, we have performed a computational time analysis, and the result has been added as a new subsection (Sec III.G), entitled “Analysis of Computational Cost”. The analysis has been
performed by measuring and recording computational times of detecting the kidney’s shape in the without-kidney and with-kidney images. We have added a new figure, as a box-plot graph, to show computational times/variations of the proposed solution and its parts, as follows,

![Fig 11. Computational times of the proposed solution’s parts.](image)

According to the reported computational times of Fig. 11, the registration part takes longer, with an average of 8.21(sec), compared to the other processing parts of the proposed solution. As can be seen in Fig. 11, the registration part has also a high variation with the standard deviation of 2.28(sec), which is due to the different iteration numbers that the registration process needs to converge among different images. The average computational time of the proposed solution, developed in MATLAB, is 12.37(sec), which is marginally acceptable for realtime interaction with paramedics. This computational time can be further reduced by combining multi-threading of CPU-cores and parallel processing using GPU-cores. Please consider the high overhead load that MATLAB puts on the computational time, as a high-level programming language. The authors believe the proposed solution will operate faster upon the preparation of the final solution, developed in a faster programming framework (i.e. CUDA and C++).

The new subsection, “Analysis of Computational Cost”, has been added in the revised manuscript in page 9, Sec III.G, 2nd column, paragraph 2, line number 9 to page 10, 1st column, paragraph 1, line number 19. For the ease of referencing, its copy is provided here:

The success of the proposed system highly relies on the real-time interaction between an operator (i.e. paramedic) and the portable solution. A desired computational time of the whole processing pipeline of the proposed computer-assisted probe placement solution is a few seconds. The computational time of the proposed solution is analyzed using the evaluation set including the with-kidney and without-kidney images. The computational time analysis of the proposed solution in whole and its parts, as described in II-D, is shown as a box-plot representation in Fig 11. Accordingly, the registration part has the largest computational time, 8.21±2.28(sec), even though it is implemented by the multi-threaded programming. Also, the computational
time variation of the registration part is higher than the other parts because the number of iterations that the registration
process takes to converge varies among different images. The mean and standard deviation of the overall computational time
is $\mu=12.37\text{(sec)}$ and $\sigma=2.84\text{(sec)}$, which is marginally acceptable for the real-time operation. The computational time of the
registration part can be reduced by combining the “parfor” and “gpuArray”, which is attainable by assigning each GPU-core
to a single thread in the parfor loop [39].

We also have modified the subsection III.C, entitled “Software and Hardware Setup”, to explain that
a portable workstation can be afforded with a moderate budget for the proposed solution, in page 7,
2nd column, paragraph 3, line numbers 21 to 29. For the ease of referencing, the modified subsection is
copied here,

The proposed solution is developed using MATLAB R2015b. To accelerate the computations, the proposed or gans detection
and localization method is developed with the MATLAB parallel processing (parfor) and GPU programming (gpuArray). A
fast workstation computer is used with an Intel Xeon E5-1660 processor with 16 cores of 3.00 GHz, and a NVIDIA Quadro
K2200 video card. A comparable configuration is affordable in a portable format (ex. DELL precision mobile workstation) with
a moderate budget. The proposed probe placement is intended to be used with a true 3D ultrasound imaging device, which is
currently under development [1].

In addition, a new paragraph has been added in the revised manuscript to discuss the reported com-
putational time of the proposed solution, in Page 11, Sec IV, 2nd column, paragraph 2, line number 11
to 33. For the ease of referencing, the new paragraph is reproduced here,

The computational time of the proposed method has a vital importance for the proposed solution to be successfully applied
in emergency healthcare. Since the proposed solution is under development, it has been developed in MATLAB, which simplifies
and accelerates the entire process of assessing a concept idea from its design through its evaluation. However, the overhead
computational load might de-emphasize the utility of the proposed solution in the real-time interaction with an operator. To
minimize the computational time, the proposed method has been developed by considering the following tricks: 1) avoiding
the use of nested loops, 2) using built-in MATLAB functions, 3) utilizing GPU-powered MATLAB functions to perform highly
parallelizable/non-complicated computations, and 4) using multi-threading multi-core capability of MATLAB to speed up com-
plicated computations (i.e. the proposed registration method). The reported computational times of the entire processing pipeline
and the parts of the proposed solution indicate that the proposed solution has the potentials to be used in real-time operations,
though, it needs more efforts to reduce the current computational time. The proposed solution can be run on portable workstations
supporting Intel-Xeon mobile processors and NVIDIA Quadro graphic processors.
III. REVIEWER 2 COMMENTS

(REV2) The authors appear to have addressed most of the problems found in the previous submission and the paper is now in a much better form.

Answer to (REV2): The authors would like to appreciate the positive feedback of the second reviewer.

IV. REVIEWER 3 COMMENTS

(REV3) The author has well responded to comments / questions from the reviewers.

Answer to (REV3): The authors would like to appreciate the positive feedback of the third reviewer.
Computer-Assisted 3D Ultrasound Probe Placement for Emergency Healthcare Applications

Abstract—In this paper, a new computer-assisted ultrasound probe placement system is introduced to guide paramedics and first responders to conduct abdominal ultrasound imaging for diagnosing trauma patients in emergency situations where specialists are not present. Recently, tele-Sonography has been employed to supervise paramedics by remote experts to perform ultrasound scan for triaging, although its utility is limited by unavailability of fast internet connectivity in remote regions. In the proposed solution of this paper, a paramedic is first instructed to place the ultrasound probe on an initial placement for imaging an organ of interest. Then, a 3D ultrasound image is acquired and processed to determine the organ’s shape misalignment with respect to a reference alignment. Afterward, the organ’s shape misalignment is used to estimate the probe misalignment, and then, a probe placement command is generated to guide the paramedic. This process iterates until a correct organ’s view of interest is obtained. As the advantage of the proposed solution over the existing technique, the proposed solution does not require a fast internet connectivity and a dedicated remote specialist to conduct ultrasound imaging by a paramedic. The utility of the proposed solution is evaluated for a case study on specialists to conduct ultrasound imaging by a paramedic. The recorded images were sent to a reference hospital where the images were screened for experts to remotely guide the paramedics to conduct diagnosis. In another attempt, Ogedegbe et al. [12] applied tele-Sonography for moving ambulances, in which two paramedics performed ultrasound scans, and acquired images were sent to an expert to remotely conduct ultrasound imaging and triaging. Although there are indications of success in the use of tele-Sonography for triaging, its utility in emergency situations faces two limitations: (1) tele-Sonography requires fast and reliable internet connectivity, which is not usually accessible in remote regions; and (2) a free expert might not be available to remotely conduct diagnosis when a patient requires triage. Consequently, tele-Sonography is deemed impractical when a large number of patients need rapid triaging (e.g., natural disasters and massive vehicular collisions [8]).

This paper introduces a computer-assisted ultrasound probe placement method, which can be installed as a software module in an ultrasound research platform. In the proposed solution of this paper, anatomical knowledge of shape and alignment of internal organs are fed into the process of ultrasound imaging to facilitate rapid diagnostic assessment of trauma patients by paramedics who lack anatomical knowledge. By recording a volumetric region (3D image) and by detecting the relevant anatomical structure of interest, rapid diagnostic assessment by paramedics is possible. The recorded 3D image of the relevant anatomical structure of interest can be sent to a referral center or a computerized diagnostic module to make a decision. Noteworthily, because the proposed solution does not need the live-streaming of ultrasound images, and merely a final 3D image of the organ is enough to be sent to a remote expert for making a diagnostic decision, a

I. INTRODUCTION

Due to recent advancements in three-dimensional (3D) ultrasound imaging [1]–[3], its utility has expanded into emergency medicine and healthcare [4]. Specifically, ultrasound imaging is the most popular tool to scan abdominal organs for triaging trauma patients [5]. The use of ultrasound imagery is preferred for emergency diagnosis over other popular imaging modalities, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), because ultrasound imaging provides the following advantages: (1) ultrasound imaging does not impose any risk to patients; (2) since ultrasound devices are portable, unstable patients are not required to be moved from a resuscitation room to an imaging room; (3) ultrasound imaging provides immediate results, which accelerates triaging [6]. Two-dimensional (2D) ultrasound imaging is widely used by radiologists for imaging abdominal organs. In contrast, 3D ultrasound is less popular, especially in abdominal scans, because its data structural complexity makes it difficult for radiologists to interpret. However, localizing internal organs in the 3D space is only possible using 3D ultrasound, which is essential for new computer-assisted methods [7]. Also, 3D ultrasound imaging offers other advantages compared to 2D ultrasound in terms of accuracy and reliability [6].

In ultrasound imaging for triaging, regions around abdominal organs are scanned to find indications of internal bleeding and abnormalities. To view abdominal organs with an ultrasound probe, a high level of anatomical understanding and knowledge is required. Therefore, a well-trained radiologist is needed to conduct abdominal ultrasound scans for triaging. Although skilled radiologists and advanced imaging devices are available at referral hospitals where patients are in hemodynamically stable conditions, these facilities are not usually accessible in emergency situations such as resuscitative bedside, pre-hospital environments, and smaller referral centers [8], resulting in a large number of preventable deaths [9].

Some researchers have attempted to provide emergency healthcare services for remote locations using tele-Sonography, in which acquired ultrasound images by paramedics are sent via internet to referral centers where the images are screened for experts to remotely guide the paramedics to conduct diagnosis [10]–[13]. Boniface et al. [10] reported the use of tele-Sonography for ultrasound scan, in which a paramedic performed imaging of model patients in an examination room, while the images were screened by an expert in another room to verbally guide the paramedic to correctly place the probe. In another attempt, Ogedegbe et al. [12] applied tele-Sonography for moving ambulances, in which two paramedics performed ultrasound scans, and acquired images were sent to an expert to remotely conduct ultrasound imaging and triaging. Although there are indications of success in the use of tele-Sonography for triaging, its utility in emergency situations faces two limitations: (1) tele-Sonography requires fast and reliable internet connectivity, which is not usually accessible in remote regions; and (2) a free expert might not be available to remotely conduct diagnosis when a patient requires triage. Consequently, tele-Sonography is deemed impractical when a large number of patients need rapid triaging (e.g., natural disasters and massive vehicular collisions [8]).
low-speed internet connectivity suffices. Alternatively, in the absence of a remote expert or the unavailability of an internet connectivity, automated diagnosis can be utilized to make a diagnostic decision. We re-emphasize that this paper’s focus is on computer-assisted ultrasound probe placement.

Some researchers have applied ultrasound probe navigation for computer-assisted surgery aiming to improve accuracy and speed of operations [14], [15]. These methods fuse sensors’ information and/or different modality images (such as CT) with the ultrasound data to estimate the probe alignment. These methods rely on pre-operational calibrations, device settings, and equipment installations, making them impractical in emergency situations. Vosburgh et al. [15] adopted an inter-modality technique to show the location of the ultrasound scan on a patient’s CT model as a highlighted region. Using positioning sensors, the probe alignment is tracked and used to register the imaged region by the ultrasound probe on the CT model. Although this technique helps paramedics in ultrasound imaging, it requires acquisition and segmentation of a 3D CT image for each patient, which is infeasible in triaging.

In the proposed solution of this paper, the ultrasound probe is navigated by processing 3D ultrasound images, without using information of positioning sensors or another imaging modality. This is essential for triaging since spending an extra time for additional settings and calibration costs patients’ lives.

The proposed solution consists of two phases: (1) initial ultrasound probe placement, and (2) correcting probe placement. In the first phase, animated graphics are visualized for the operator to place the ultrasound probe on a proximity of the organ of interest. This step is essential because it maintains a partial visualization of the organ of interest in acquired 3D images. Upon the completion of the first phase, 3D images are acquired and processed to detect and locate the organ of interest, and probe realignment commands are sent to the operator until the organ’s alignment matches with a reference. Thus, organ detection is at the heart of the proposed solution.

Abdominal organ detection in 3D ultrasound has been addressed rarely by researchers [7], [16], because processing of 3D ultrasound images faces the following challenges:

- **Ultrasound-specific challenges**: Speckle noise degrades the quality of images. Low contrast and inconsistent intensity profile reduces the separability of organs from their surrounding regions [17].

- **Organ-specific challenge**: Due to the adjacency of organs with high scattering tissues, shadows may partially occlude the organs, leading to incorrect decisions [7].

- **Operator-specific challenge**: Misalignment of the ultrasound probe due to operators’ inexperience results in partial organ visualization, which may cause a mis-characterization of the organ’s shape [7].

Noll et al. [16] proposed a method to detect the right kidney in 3D ultrasound images based on a searching strategy. This method searches along radial rays to find kidney boundaries. This method simplifies the kidney anatomical structure into an elliptical shape, resulting in false detections. In another attempt, Marsoussi et al. [7] reported the shape-based kidney detection method in 3D ultrasound images. In this method, a kidney shape model is generated from a training set, and it is used to find a location inside a 3D ultrasound image with the maximum cross-correlation metric. The method in [7] is prone to fail when the organ shape in an acquired image is deformed by orientation and scaling, with respect to a reference shape.

As a part of the proposed solution in this paper, a new shape-based method is represented to detect abdominal organs in 3D ultrasound images. For an organ of interest, a shape model is generated based on an organ’s anatomical structure and statistical representation of the organ’s shape variability. The anatomical knowledge provides higher specificity of organ detection, while statistical representation provides more tolerance against local deformations of the organ’s shape in input images. To address the ultrasound challenges, an organ-specific pre-processing module is designed that enhances a 3D ultrasound image, in which organ’s candidate voxels are featured from other voxels. To detect an organ’s shape, its model is rigidly registered via an affine transform on the enhanced image, to find the best match of the shape model with the image data. We introduce a new registration metric to improve the robustness of an organ’s shape detection against a partial organ’s shape deformation and occlusion. More specifically, the paper’s contributions are as follows:

- **System-level contribution**: A computer-assisted probe placement is designed as a software add-on. The developed module can be installed on an ultrasound research platform and used to assist paramedics and first responders in their diagnosis of trauma patients.

- **Theoretical contributions**:
  1. A registration method is introduced based on a new similarity metric to detect organs in the presence of an organ’s shape deformation and partial occlusion.
  2. A new organ’s shape model is represented by combining anatomical structure and shape variability of an organ of interest.
  3. A preprocessing module is designed to address the ultrasound-specific challenges including speckle noise, low-contrast, and inhomogeneous intensity profile of 3D ultrasound images.

The rest of the paper is organized as follows: in section II, processing pipelines of probe navigation and organ detection are introduced. Section III represents experiments of the proposed solution for abdominal trauma detection. In section IV, the reported results are discussed, and finally, the conclusion and future work are provided in section V.

### II. Methodology

The objective of the solution proposed in this paper is to guide paramedics to find a correct ultrasound probe placement for imaging an abdominal organ of interest. The concept of the proposed solution is to feed anatomical knowledge of the organ’s location and shape into the imaging process to compensate for the lack of anatomical knowledge of paramedics. The process of probe placement consists of two phases: initial probe placement, and correcting probe placement.

In the first phase, anatomical knowledge of the organ’s location is used to guide a paramedic to place the ultrasound probe on a location on a patient’s skin, which minimizes the...
probe misalignment with respect to a correct probe alignment for imaging the organ of interest. The human anatomy differs by age and gender among patients, and to correctly guide paramedics to find an initial probe placement, the age and gender of patients should be specified. Based on the age and gender of a patient, an anatomical model in the supine position is displayed, and graphical instructions of initial probe placement are shown on the anatomical model (Fig. 2). The first phase continues until the paramedic gives a confirmation signal of completing initial probe placement (CSoCIPP). Sec. II-A introduces an example of initial probe placement for imaging the RUQ view, which is necessary for diagnosing abdominal trauma patients [18]. Due to inexperience of paramedics and human anatomy variability among patients, initial probe placement only provides a partial organ visibility in an acquired 3D image. Hence, further adjustments are required to obtain a correct organ’s view.

Upon receiving the CSoCIPP signal, the second phase starts to fine-tune the ultrasound probe alignment for imaging the organ of interest. In the second phase, a process of probe realignment is iterated until the correct probe placement is obtained. Each iteration consists of image acquisition, image processing to detect the organ, calculating probe misalignment, sending a probe navigational command, and waiting for the paramedic’s confirmation. An iteration begins with acquiring a 3D ultrasound image, and the acquired image is processed to detect and locate the organ’s shape inside the image. If the organ is not detected, the paramedic is referred back to redo the first phase. Otherwise, the alignment of the detected organ’s shape is compared with a reference shape alignment to find the organ’s shape misalignment in the acquired 3D image. Because the alignment of the organ’s shape inside images is directly linked to the ultrasound probe alignment, the calculated organ’s shape misalignment is used to estimate its corresponding ultrasound probe misalignment (Sec. II-C). After estimation of the ultrasound probe misalignment, a navigational command is sent to the paramedic to move or rotate the probe toward the correct placement. Afterward, the process waits for a confirmation signal of performing probe realignment (CSoPPP) from the paramedic. Then, the process of the second phase continues with the next iteration until a correct view is obtained. The processing pipeline of the proposed computer-assisted ultrasound probe placement is represented in Fig. 1. The proposed computerized 3D ultrasound probe placement consists of:

- **Initial probe placement**: for an organ of interest, anatomical knowledge of the organ’s location is applied to instruct paramedics how to align the ultrasound probe on an initial placement to minimize the probe misalignment with respect to a correct view.
- **Organ detection and localization**: anatomical knowledge of an organ’s shape is used to detect and localize the organ’s shape in acquired 3D ultrasound images.
- **Calculating probe misalignment**: based on a calculated organ’s shape misalignment in an acquired 3D image with respect to a reference alignment, a probe misalignment is calculated to generate probe navigational commands.

In the rest of this section, initial probe placement is described by an example in Sec. II-A, and afterward, organ detection and localization, calculating probe misalignment, and the implementation of the proposed solution are introduced.

### A. Example of Initial Probe Placement - RUQ View

The RUQ view, also called the Morison’s pouch view, is very important for triaging since it provides the highest sensitivity to most abdominal bleeding [18]. In this view, the right kidney and a portion of the liver are visualized. Shokoohi et al. [19] have shown that the intersection of the horizontal sub-xiphoid and right midaxillary lines optimizes probe placement for the RUQ view. According to [19], the probe marker should be directed toward the cephalad. Based on [19], we created animations to guide paramedics to locate the initial probe placement of the RUQ view (a frame of the animations, for a mid-age male model, is shown in Fig. 2).

### B. Organ Detection and localization

Because paramedics do not have enough anatomical knowledge of organs’ shapes, they cannot discriminate an organ of interest from other tissues/organs inside acquired 3D ultrasound images, and consequently, they are not able to decide when a correct view of the organ is achieved. To facilitate correct ultrasound probe placement for imaging an organ of interest by paramedics, anatomical knowledge of the organ’s
shape is fed into the process of the organ’s shape detection and localization to automatically decide:

- Does the organ’s shape exist in a 3D ultrasound image?
- Is the organ’s shape misaligned with respect to a reference organ’s shape alignment?
- What is the organ’s shape misalignment in terms of translation and orientation?

In this paper, a shape model for an organ of interest, representing anatomical knowledge of the organ’s shape, is generated and used to detect and localize the organ of interest in 3D ultrasound images. For a 3D ultrasound image, the organ’s shape model is rigidly registered on the image data to find the best matching of the shape model with the organ’s shape in the image. However, due to the ultrasound-specific challenges, quality of ultrasound images is low, which can result in incorrect organ’s shape registration. Therefore, we designed a preprocessing approach to overcome the ultrasound challenges with a low computational cost to be used in real-time triaging. In the following paragraphs, the proposed preprocessing, generating an organ’s shape model, and shape registration are discussed in detail.

1) Preprocessing: To avoid incorrect shape registration due to the ultrasound challenges, we propose an organ-specific preprocessing, consisting of four elements: (1) reducing image resolution to accelerate computations, (2) applying a FIR filter to reduce speckle noise, (3) using local histogram equalization to improve the intensity contrast, and (4) utilizing global and local thresholding to overcome the intensity inhomogeneity.

Because the proposed solution will be used in real-time triaging, minimizing the computational time of organ’s shape detection and localization is necessary. Down-sampling 3D ultrasound images reduces computational costs of preprocessing and registration by the order of \( \text{res}^3 \), where \( \text{res} \) is the down-sampling ratio. Assume that \( V^{in} \in \mathbb{R}^{S_x \times S_y \times S_z} \) is an input 3D image, and its down-sampled version is \( V^{res} \in \mathbb{R}^{S'_x \times S'_y \times S'_z} \). The down-sampling ratio should be selected as the lowest possible value that does not obscure structural details of the organ’s shape. Many factors are involved in selecting an optimized value of \( \text{res} \): they include quality and resolution of acquired images, and structural complexity and size of the organ’s shape inside acquired images. One way to select \( \text{res} \) is to reduce it as much as possible, ensuring that the organ of interest remains clearly detectable by human eyes.

Speckle noise has been known as the main challenge in ultrasound image processing, and speckle noise reduction has been investigated by many researchers [20]–[22]. However, most of them are either computationally demanding or impractical for enhancing 3D ultrasound images, and therefore, they are not applicable in the proposed solution of this paper. In this paper, we design speckle reduction using finite impulse response (FIR) filtering because it provides the fastest possible denoising. Instead of designing a single denoising filter for detecting all organs, we design a tunable FIR filter that maximizes efficiency and strength of image denoising for each organ of interest. The applied FIR filter is generated by multiplying a 3D Gaussian function (with zero mean and standard deviation \( \sigma_G \)) and a rectangular window (with the width of \( N_{\text{Rect}} \)) [23]. This combination is selected because the Gaussian function is both separable and isotropic, and therefore, it reduces the computational complexity by simplifying 3D convolution of order \( O(N^3) \) into three one-dimensional convolutions of order \( O(N) \). The two parameters, \( \sigma_G \) and \( N_{\text{Rect}} \), are set to optimize denoising for each organ of interest. Increasing \( \sigma_G \) provides more noise suppression at the cost of blurring the organ’s shape. Thus, for each organ of interest, we need to find the maximum of \( \sigma_G \) that ensures the internal structure of the organ is not obliterated by the blurring effect.

Assume for an organ of interest, two parts of its internal structure are apart from each other by an average minimum distance of \( W_{\text{min}} \) inside 3D images of the resolution, \( \text{res} \), as shown Fig. 3a. Also, we consider intensities \( C_1 \) and \( C_2 \), where \( C_2 > C_1 \), for the middle dark and bright regions, respectively. For the middle point, as shown in Fig. 3b, we set a constraint that after denoising, its intensity level should not exceed \( \frac{1}{4}C_1 + \frac{1}{2}C_2 \) to ensure that it remains distinctive from the bright regions. This constraint maintains that after denoising, the bright regions in Fig. 3b are separable from each other, and thus, the organ’s structure is not obscured by filtering. Thus, we obtain \( S_1 + 2S_2 \leq \frac{1}{4}C_1 + \frac{1}{2}C_2 \), where \( S_1 \) and \( S_2 \) are specified in Fig. 3b, and can be approximately calculated using the error function, \( \text{erf} \), as, \( S_1 = C_1 \text{erf}(\frac{W_{\text{min}}}{2\sqrt{2\sigma_G}}) \) and \( S_2 = 0.5C_2(1 - \text{erf}(\frac{W_{\text{min}}}{2\sqrt{2\sigma_G}})) \). By replacing \( S_1 \) and \( S_2 \) in the constraint, we obtain \( \text{erf}(\frac{W_{\text{min}}}{2\sqrt{2\sigma_G}}) \geq 0.5 \), which results in \( \sigma_G \leq 0.7414W_{\text{min}} \). The maximum allowable smoothness is achieved by \( \sigma_G = 0.7414W_{\text{min}} \). Finally, we set \( N_{\text{Rect}} \) as the nearest odd number to \( 4\sigma_G \) to cover about 95% of the Gaussian function inside the rectangular window. By filtering \( V^{res} \) using the organ’s specific filter, we obtain \( V^{dn} \). The process of filtering acquired images for an organ of interest is summarized as follows:

- Selecting a proper resolution, \( \text{res} \), for down-sampling acquired images,
- Measuring \( W_{\text{min}} \) for the organ’s shape in the image resolution \( \text{res} \),
- Calculating \( \sigma_G \) and \( N_{\text{Rect}} \).

The denoised image still suffers from a low-contrast intensity profile that reduces separability of the organ of interest from its surrounding tissues. To address this challenge, localized histogram equalization (LHE) is applied to achieve an enhanced volume, \( V^{\text{LHE}} \), with an improved intensity contrast that makes the organ’s shape more separable from its surrounding tissues. LHE uses a local transformation for
each voxel based on the cumulative density function (CDF) in a vicinity of length $N_{LHE}$, which expands highly concentrated intensity levels in the histogram, and vice versa [24]. The reason for using local histogram equalization, instead of applying histogram equalization, is that the intensity profile of an organ’s shape is unevenly distributed throughout the 3D image, and thus, for each local region, a different intensity transformation is required. Since LHE calculates CDF for each single voxel in the 3D image, it is computationally demanding. Thus, to reduce computational time of LHE, it is implemented using parallel processing (see Sec. II-D).

The contrast enhanced image, $V^{LHE}$, still suffers from an inhomogeneous intensity profile that can reduce the organ detection accuracy. To overcome this challenge, we apply a combination of global and local thresholding methods using the multi-Ostu [25] and the ordinary Kriging indicator [26] to classify voxels into tissue and non-tissue classes. The multi-Otsu method finds two global threshold values $T_0$ and $T_1$, and voxels with intensity levels less than $T_0$ and greater than $T_1$ are immediately assigned with $-1$ and $1$ labels, respectively. Voxel intensity levels between $T_0$ and $T_1$ are labeled using the ordinary Kriging method. The ordinary Kriging method applies stationary spatial covariance and ordinary Kriging indicator at each voxel to incorporate intensity information of its neighbor voxels, and calculates the voxel’s probability of belonging to each of the classes. The output image is $\{V^{eh}|V^{eh}(X)\in[-1,1]\}$. The block diagram of the organ-specific preprocessing is shown in Fig. 4.

![Fig. 4: The block diagram of the organ-specific preprocessing.](image)

2) **Organ's Shape Model Generation**: We introduce a method to generate a shape model for an organ of interest based on anatomical knowledge of the organ’s shape and statistical representation of the organ’s shape variability. For an organ of interest, its shape model is defined by an implicit representation to model the organ’s anatomical structure. The implicit representation provides a mapping from the 3D domain of the organ’s shape model into a scalar value specifying memberships of voxels. Although the representation of shape model of this paper might look similar to the implicit representation commonly used in level-set framework [27], there is a significant difference between them that makes the shape model of this paper to be more effective for detecting organs rather than for segmenting organs. In the level-set representation, an iso-surface of a segmented region is outlined by zero-level voxels, and voxels inside and outside the segmented region are defined by positive and negative values, respectively [27]. However, in the shape representation of this paper, non-organ voxels are set to zero, the organ voxels are assigned with a statistical value in the range $[0, 1]$, and outer and inner boundaries of the organ are assigned with a negative value, $\varphi_{Neg}$, such that the integral of the entire shape model is zero. This definition helps the shape registration process (Sec. II-B3) to achieve a more accurate fitness by pushing negative valued voxels, belonging to organ’s boundary, out of the organ’s shape of $V^{eh}$, while pulling positive valued voxels of the organ’s shape model inside the organ’s shape of $V^{eh}$.

In this paper, anatomical knowledge of an organ’s shape is collected from a training set of 3D ultrasound images containing the organ of interest. The organ’s shape is manually outlined in each image of the training set by a person who has anatomical knowledge and understanding of abdominal organs in ultrasound images. Each outlined shape is a 3D binarized image, $\{B^i_{tr}\in \mathbb{R}^{Sx}\times Sy\times Sz} | i \in \{1, \ldots, N_{tr}\}\}$, in which organ and non-organ voxels are labeled by one and zero, respectively. Once the training set of the organ of interest is ready, a shape is selected as a reference, $B^{ref}_{i}$, and other shapes are rigidly registered on the reference shape, $B^i_{reg}$. Finally, the average of the registered shapes are calculated as the statistical representation of the organ’s shape, as $\varphi(X) = \sum_{i=1}^{N_{tr}} \varphi_{reg}(X_{i}) / N_{tr}$, where $X$ defines coordinates of a voxel in the 3D domain of the organ’s shape model. For registration, the affine transformation is used because it only deforms binarized images by translation, orientation, and scaling, and hence, the statistical representation of the organ’s shape variability as a non-rigid deformation is kept in $\varphi(X)$.

After calculating $\varphi(X)$, voxels belonging to inner and outer boundaries of the organ’s shape are assigned with a negative value, $\varphi_{Neg}$. We use morphological operators to find the organ’s shape boundary. First, a thresholded image is obtained as $\varphi_{th}(X) = \{\varphi(X) > 0\}$. Then, a dilation operator with a disk radius of $N_{dil}$ pixels is applied on the thresholded image to obtain $\varphi_{dil}(X) = \text{dilate}(\varphi_{th}(X))$. Afterward, the dilated image is subtracted by the thresholded image to achieve $\varphi_{Bnd}(X) = \varphi_{dil}(X) - \varphi_{th}(X)$. Voxel belonging to the organ’s shape boundary are ones in $\varphi_{Bnd}$. The width of the organ’s shape boundary is controlled by $N_{dil}$. The organ’s shape model is obtained by $\Phi(X) = \varphi(X) + \varphi_{Neg} \times \varphi_{Bnd}(X)$, where $\varphi_{Neg} < 0$. The block diagram of the organ’s shape model generation is shown in Fig. 5.

![Fig. 5: The block diagram of organ’s shape model generation.](image)

3) **Registration**: We apply rigid registration of the organ’s shape model on the enhanced image to detect and localize the organ’s shape in acquired ultrasound images. In an acquired image in which the probe is not properly aligned, the organ of interest is partially aligned out of the ultrasound window,
resulting in partial organ's shape visibility (Operator-specific challenge), which may prevent registration to detect the organ's shape. Some researchers have investigated image registration under the presence of an object occlusion [28]–[30]. Kaneko et al. [28] proposed the selective cross-correlation (SCC), which masks non-concordant pixels in template and image from calculating its similarity metric, aiming to detect occluded objects. In the SCC method, mask coefficients are generated based on the data consistency between template and image for each pixel. In ultrasound images, the organ’s shapes in acquired images are deformed by both rigid and elastic deformations, and therefore, checking voxels coherency between the shape model and the enhanced 3D image results in masking out most of voxels of the organ’s shape from the similarity metric calculation, leading to an incorrect registration. Thus, the SCC similarity metric is not applicable in the proposed solution. In this paper, we introduce an affine registration based on a new regularized cross-correlation (RCC) metric, which provides robust registration against shape occlusion and elastic deformation of the organ of interest in 3D ultrasound images. Let us define the affine transformation as \( T_{af} \) with nine parameters, \( T_{af} = [\theta_x, \theta_y, \theta_z, S_x, S_y, S_z, t_x, t_y, t_z] \), where \( \{\theta_x, \theta_y, \theta_z\} \) are orientation parameters, \( \{S_x, S_y, S_z\} \) are scale parameters, and \( \{t_x, t_y, t_z\} \) are translation parameters. The objective is to maximize RCC metric as,

\[
\tilde{p}_{af} = \max_{\tilde{p}_{af}} \left\{ \frac{1}{\Omega X} \sum_{Y \in \Omega Y} B(\tilde{X} + \tilde{Y}) \Phi(T_{af}^{-1} \cdot \tilde{Y}) \right\} 
\]

and,

\[
\Lambda(\tilde{X}, \tilde{p}_{af}) = \left\{ K + \sum_{Y \in \Omega Y} V_{LR+}(\tilde{X} + \tilde{Y}) \Phi^+(T_{af}^{-1} \cdot \tilde{Y}) \right\}^{-1}
\]

where \( \Lambda(\tilde{X}, \tilde{p}_{af}) \) is the regularization factor, \( \Omega \) is the 3D domain of the 3D enhanced image, \( \Omega \) is the 3D domain of the organ’s shape model, and \( \Phi^+ \) satisfies \( \Phi(\tilde{Y}) > 0 \) thresholds the shape model to equalize all voxels belonging to the organ’s shape in \( \Phi \). \( V_{LR+}(\tilde{X}) = \{V_{LR}(\tilde{X}) \geq 0 \} \) thresholds the resolution adjusted image to specify voxels inside the ultrasound pyramidal window. \( K \) prevents the maximization problem of equation (1) to give trivial answers when the intersection of \( \Phi^+ \) and \( V_{LR+} \) has a small value. The regularization factor boosts the RCC metric at points where the organ’s shape model is partially aligned out of the ultrasound pyramidal window. In equation (1), the inner maximum finds a location \( \tilde{X} \in \Omega \) with the maximum RCC for a specific \( \tilde{p}_{af} \). The outer maximum searches for a \( \tilde{p}_{af} \) that maximizes the calculated maximum RCC in the inner maximum. We use the gradient descent method to solve equation (1) \([31]\), in which 12 updating vectors are utilized to iteratively modify orientation and scaling parameters in \( \tilde{p}_{af} \), aiming to move toward an optimum solution. The affine parameters are initialized by \( \tilde{p}_{af} = [0, 0, 0, 1, 1, 1, 0, 0, 0] \). The updating vectors are \( \tilde{e}_{112} = [\pm \delta t_x, 0, 0, 0, 0, 0, 0, 0, 0] \), \( \tilde{e}_{34} = [0, 0, \pm \delta t_y, 0, 0, 0, 0, 0, 0] \), \( \cdots \) \( \tilde{e}_{1112} = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0] \). We empirically set \( \delta t_x = \delta t_y = \delta t_z = \frac{\pi}{2} \) and \( \delta s_x = \delta s_y = \delta s_z = 0.1 \). After the iterative process converges into the maximum RCC, the affine translation parameters are set to \( [t_x, t_y, t_z] = \tilde{X}^* - \tilde{X}^{des} \).
Algorithm 1: Calculating the Probe Projection Matrix

begin
Select patient model and 3D ultrasound device;
Initialize: \( T_{kp} = \text{eye}(4) \) for \( k \in \{1, 2, 3, 4\} \) where \( \text{eye}(4) \) is an identity matrix of size \( 4 \times 4 \);
Step-1: Find the Morison’s pouch view;
Step-2: Move (slide) the probe slightly toward cephalad direction, record the movement as \( T_{kp}^{1}(1, 4) \), acquire a 3D image, and calculate and save it as \( T_{kp}^{1} \);
Step-3: Return the probe back to the Morison’s pouch view, and move (slide) the probe slightly towards caudal direction, record it as \( T_{kp}^{2}(1, 4) \), acquire a 3D image, and calculate and save \( T_{kp}^{2} \);
Step-4: Return the probe back to the Morison’s pouch view, rotate the probe (clockwise), record it as \( T_{kp}^{3}(1 : 3, 1 : 3) = R_{\theta_{k}} \) where \( R_{\theta_{k}} \) is the rotation matrix of probe \( \theta_{k} \), acquire a 3D image, and calculate and save \( T_{kp}^{3} \);
Step-5: Return the probe back to the Morison’s pouch view, rotate the probe (counter-clockwise), record it as \( T_{kp}^{4}(1 : 3, 1 : 3) = R_{\theta_{k}} \) where \( R_{\theta_{k}} \) is the rotation matrix of probe \( \theta_{k} \), acquire a 3D image, and calculate and save \( T_{kp}^{4} \);
Step-6: Calculate \( T_{kp} \) using equation (3).
end

acquired 3D images, and display ultrasound probe navigational commands. The 3D ultrasound images are displayed by multiplanar reformatting and ray-casting techniques [34]. In addition, the GUI provides an easy way for paramedics to give the CSoCIPP and CSoPPR signals (Sec. II).

The proposed organ detection method has a massive computational load, and the computational time should be minimized to be applicable in realtime interaction with a paramedic for triaging. The total computational time of the proposed organ detection is the summation of the computational times of the following parts: 1) noise reduction with Gaussian-Rectangular FIR filters, 2) local histogram equalization, 3) global and local thresholding, 4) rigid registration of the organ shape model, and 5) calculating the probe misalignment. The computational time of calculating the probe misalignment is very small, and therefore, it is not included in the analysis. Table I shows three types of the applied implementation methods to develop the parts in MATLAB R2015b, including the single-core sequential programming “Single-thread”, multi-threaded programming with multicore “parfor”, and GPU accelerated parallel programming “gpuArray”. For accelerating the preprocessing task, GPU programming is adopted to accelerate FIR filtering and local histogram equalization. For accelerating the registration process, each iteration is split into 12 threads, and each thread is dedicated for a single updating vector. Thus, the computational time of registration is reduced by \( \frac{1}{12} \).

| TABLE I: Implementation methods of the parts of the proposed solution in MATLAB. |
|-----------------------------------------------|-----------------|----------------|
| Specle Reduction | Single-thread | parfor | gpuArray |
| Local Histogram Equalization | ✓ | ✓ | ✓ |
| Global and Local Thresholding | ✓ | ✓ | |
| Registration | ✓ | ✓ | |

III. EXPERIMENTAL RESULTS

To evaluate and prove the utility of the proposed solution of this paper in emergency healthcare (i.e. diagnosing trauma patients), the proposed method has been developed using MATLAB. Since the proposed 3D ultrasound probe placement of this paper is currently under development-experimental stage, MATLAB has been selected as a well-suited environment to develop the concept idea, to implement the mathematical formulation, and to perform experimental analysis.

A. Case Study: RUQ View

To evaluate the performance of the proposed solution, we choose the RUQ view, which has a vital importance in diagnosing abdominal trauma patients [18]. In this view, the right kidney is visualized; its appearance is unique among all abdominal organs in 3D ultrasound images. The anatomical knowledge of the right kidney’s location is used to provide a graphical guide for paramedics to initially place the ultrasound probe on the intersection of the horizontal sub-xiphoid and right midaxillary lines, with the probe’s marker oriented toward the cephalad direction (Sec. II-A). The anatomical knowledge of the right kidney’s shape is generated using six 3D ultrasound images, manually segmented using Turtle-seg [35]. The segmented kidney’s shapes, \( \{B_{i}^{k} | i \in [1, ..., 6]\} \), are used to generate the right kidney’s shape model, \( \Phi \). The performance of navigating the ultrasound probe for grabbing a correct RUQ view is linked to the performance of the kidney’s detection and localization. Thus, the focus of experiments in this paper is on evaluating accuracy and robustness of the proposed organ’s detection and localization method, applied on the right kidney. Assessing precision and required time of initial probe placement is out of the scope of the experiments of this paper. Instead, we investigate the tolerance of the proposed organ’s detection and localization method toward the kidney’s shape misalignment that can be caused by a paramedic’s imprecision in initial probe placement.

B. 3D Ultrasound Dataset

The validity of the evaluation depends on comprehensiveness and quality of dataset images. We have collected a set of actual 3D ultrasound images by a GE vivid ultrasound device. Using the actual 3D ultrasound images, accuracy and robustness of the proposed organ’s detection and localization method against the ultrasound-specific challenges are evaluated. However, the actual ultrasound images do not provide enough variability and capability to support assessing tolerance and robustness of the proposed method against the organ-specific and operator-specific challenges, even by increasing the number of dataset images. To overcome this lack, we developed a 3D ultrasound image simulator, mimicking actual ultrasound images of the RUQ view, which allows the proposed method to be examined under any desired combination of organ’s deformation and partial occlusion.

The actual 3D ultrasound images consist of 44 images taken from eight healthy volunteers and eight trauma patients. Fifteen images from healthy volunteers are randomly taken.
from non-RUQ views, and are labeled as “without-kidney.”

The other 29 images, which are taken from the RUQ view, are called “with-kidney”; these 21 and 8 images are taken from the healthy volunteers and trauma patients, respectively. The use of both without-kidney and with-kidney allows us to evaluate the accuracy of detecting the kidney shape using the proposed method of this paper, compared to the other methods. In patients with abdominal trauma, the free fluids around the right kidney due to bleeding change the morphology of the RUQ view. Therefore, using the images of trauma patients, the robustness of the organ’s shape detection methods against morphological changes in ultrasound images are evaluated. We have used 6 with-kidney images of healthy volunteers to generate the right kidney’s shape model, and the other 23 with-kidney images along with the 15 without-kidney images are used to evaluate the accuracy of the proposed organ’s detection method.

C. Software and Hardware Setup

The proposed solution is developed using MATLAB R2015b. To accelerate the computations, the proposed organ’s detection and localization method is developed with the MATLAB parallel processing (parfor) and GPU programming (gpuArray). A fast workstation computer is used with an Intel Xeon E5-1660 processor with 16 cores of 3.00 GHz, and a NVIDIA Quadro K2200 video card. A comparable configuration is affordable in a portable format (ex. DELL precision mobile workstation) with a moderate budget. The proposed probe placement is intended to be used with a true 3D ultrasound imaging device, which is currently under development [1].

D. Evaluation Metrics

For evaluating the organ’s detection method, the accuracy, sensitivity, and specificity measures are used as:

\[
\begin{align*}
\text{ACC}_{KD} &= (100\%) \frac{N_{TP} + N_{TN}}{N_{TP} + N_{TN} + N_{FP} + N_{FN}} \\
\text{Sens}_{KD} &= \frac{N_{TP}}{N_{TP} + N_{FN}} \\
\text{Spec}_{KD} &= \frac{N_{TN}}{N_{TN} + N_{FP}}
\end{align*}
\]

where \(N_{TP}, N_{TN}, N_{FP}, \text{ and } N_{FN}\) are numbers of true positive, true negative, false positive, and false negative detections, respectively. A true positive (TP) detection refers to a RCC outcome of a with-kidney image that \(\Gamma^* > \Gamma^{th}\) and \(d = \|\hat{X} - \hat{X}^{ac}\|_2 < d_{max}\) where \(\hat{X}^{ac}\) and \(d_{max}\) are the detected organ’s shape center, actual organ’s shape mass center, the Euclidean distance error of the detected and actual organ’s centers, and maximum acceptable Euclidean distance error, respectively. For a with-kidney image, if \(\Gamma^* > \Gamma^{th}\) but \(d > d_{max}\), then the detection is a false positive (FP). Also, for a without-kidney image, if \(\Gamma^* > \Gamma^{th}\), the detection is a FP. For a with-kidney image, if \(\Gamma^* < \Gamma^{th}\), the detection is a false negative (FN), and for a without-kidney image, if \(\Gamma^* < \Gamma^{th}\), the detection is a true negative (TN). We set \(d_{max} = 35\) to ensure that the detected organ’s shape centers of TP detections are located inside the kidney shape. For each with-kidney image, the actual organ’s shape mass center is provided as ground-truth data.

E. Evaluating and Comparing Kidney Detection Methods

In this experiment, the proposed organ’s detection method is evaluated for the case study of the RUQ view, and it is compared with two state-of-the-art kidney detection methods in 3D ultrasound images, including Marsouei-EMBC14 [7] and Noll14 [16]. The accuracy and sensitivity metrics are calculated for the following subsets of medical images:

- **Healthy volunteers**: 15 with-kidney images and 15 without-kidney images
- **Trauma patients**: 8 with-kidney images

The specificity measure is only calculated for the sub-set of healthy volunteers containing 15 without-kidney images. The subset of trauma patients does not contain any without-kidney image, and therefore, calculating the number of false-positive detections is meaningless. The kidney detection results for both subsets of images are demonstrated in Table II. The reported results in Table II show that the proposed method in this paper provides the highest accuracy of \(\text{ACC}_{KD} = 90.00\%\) and \(\text{ACC}_{KD} = 75.00\%\) for the subsets of healthy volunteers and trauma patients, respectively. According to Table II, the detection accuracy for the subset of trauma patients is lower than for the subset of healthy volunteers, because the right kidney’s shape and its surrounding tissues in the RUQ view of trauma patients appear distorted in the 3D ultrasound images compared to those of the normal subjects, resulting in excessive complexity of the organ’s detection. The proposed method in this paper provides the highest sensitivity \((\text{Sens}_{KD} = 0.9333)\) and specificity \((\text{Spec}_{KD} = 0.8667)\) of organ’s shape detection among the other methods. Compared to the proposed method of this paper, the Marsouei-EMBC14 method has obtained a lower detection accuracy \((\text{ACC}_{KD} = 83.33)\), because Marsouei-EMBC14 is not robust against organ’s shape deformations. The Noll14 has obtained the detection accuracy of \(\text{ACC}_{KD} = 63.33\) because it is sensitive to the kidney occlusion due to shadows and ultrasound probe misalignment. Figure 7 displays 2D slices of four actual 3D images of the RUQ view, showing that the organ’s shapes are correctly detected and localized.

For further validation, the Euclidean distance errors of the detected center points, with respect to the actual center points, of the kidney shape in the with-kidney images of the healthy volunteers are compared for the three methods. We used the box-plot graph, displaying standard deviation, minimum, maximum, and outlier samples [36], [37], to visually represent the statistical variations of the obtained results, as shown in Fig. 8. The mean and standard deviation of the Euclidean distance errors of the proposed method, Marsouei-EMBC14 [7], and Noll14 [16] are \(18.8052 \pm 16.3582\) px, \(33.6812 \pm 18.9547\) px, and \(31.3152 \pm 12.5904\) px, respectively. Accordingly, the proposed method shows smaller average and median of the Euclidean distance error of the detected center points. We also perform two data analysis to show the detected center point results obtained by the proposed method is significantly better than the other methods. Because the number of samples (measured distance errors in the with-kidney images) is small, and the samples are not normally distributed, the Wilcoxon rank-sum test is used instead of the t-
In this experiment, we evaluate the accuracy and robustness of organ’s shape misalignment detectability of the proposed organ detection and localization method for the case study of the RUQ view in the presence of organ’s shape deformation and occlusion. The organ’s shape misalignment occurs due to the ultrasound probe misalignment in terms of translation and orientation over \(x\)-, \(y\)-, and \(z\)-axes. As mentioned in (Sec. III-B), the dataset of actual ultrasound images does not provide enough variability and flexibility to assess tolerance and robustness of the proposed method against organ’s shape occlusion and deformation, even by increasing the number of actual images of the dataset. Therefore, the simulated ultrasound volumes are used to facilitate the evaluation of the proposed method under any arbitrary organ’s shape deformation and occlusion. In the simulated images, the translations over \(x\)-, \(y\)-, and \(z\)-axes are defined as \(\Delta t_x, \Delta t_y, \Delta t_z\) \(\in\{-100, -98, \ldots, 98, 100\}\). Based on the nature of the ultrasound imaging, the probe orientations over \(y\)- and \(z\)-axes, so-called rocking and tilting [19] respectively, are limited to small angles, whereas the probe orientation over \(x\)-axes, so-called rotating [19], is not limited. Thus, in the simulated 3D ultrasound images of the RUQ view, the right kidney’s shape orientation over \(x\)-axis is selected form \(\Delta \theta_x \in \{-120^\circ, -118^\circ, \ldots, 118^\circ, 120^\circ\}\), and the right kidney’s shape orientation over \(y\)- and \(z\)-axes are selected from \(\Delta \theta_y, \Delta \theta_z \in \{-45^\circ, -44^\circ, \ldots, 44^\circ, 45^\circ\}\). For each of the deformation parameters \(\Delta t_x, \Delta t_y, \Delta t_z, \Delta \theta_x, \Delta \theta_y, \Delta \theta_z\), the organ’s shape visibility is measured from 0% to 100%, and the images are fed into the proposed organ’s detection and localization method. First, the proposed method tries to detect the organ’s shape in the presence of known deformation. This allows us to evaluate the detectable range of the proposed method for each deformation parameter, which is shown in Fig. 9 with dotted red lines (low for incorrect detections and high for correct detections). In Fig. 9, the organ’s shape visibility is specified with the dashed green lines. The organ’s shape visibility depends on the deformation parameters, except for the \(\Delta \theta_x\). The minimum organ’s shape visibility required to detect the organ’s shape for the deformation parameters \(\Delta t_x, \Delta t_y, \Delta t_z, \Delta \theta_y, \Delta \theta_z\) are 75%, 45%, 63%, 58%, and 54%, respectively. The proposed organ’s shape localization estimates the organ’s shape misalignment with respect to the reference shape. The estimated deformation parameters are compared with the known deformation parameters to calculate the absolute error of misalignment estimation for each of the deformation parameters. In Fig. 9, each of the graphs represents a deformation parameter, and the absolute estimation errors of the parameters are shown with blue lines. Accordingly, the absolute error of deformation
TABLE II: Comparison of the proposed kidney detection method with Marsousi (EMBC) [7] and Noll et al. [16].

<table>
<thead>
<tr>
<th>Method Name</th>
<th>Healthy Volunteers</th>
<th>Trauma Patients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$[N_{TP}, N_{FP}, N_{FN}]$</td>
<td>$N_{TP}, N_{FP}, N_{FN}$</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>14, 13, 2, 1</td>
<td>90.00</td>
</tr>
<tr>
<td>Marsousi (EMBC)</td>
<td>11, 14, 4, 1</td>
<td>85.33</td>
</tr>
<tr>
<td>Noll et al.</td>
<td>8, 11, 3, 8</td>
<td>63.33</td>
</tr>
</tbody>
</table>

Fig. 9: Displaying kidney misalignment detectability of the proposed method. Top-Left: translation over $x-$ axis, Top-Middle: translation over $y-$ axis, Top-Right: translation over $z-$ axis, Bottom-Left: orientation along $x-$ axis (rotating), Bottom-Middle: orientation along $y-$ axis (rocking), Bottom-Right: orientation over $z-$ axis (tilting). The dotted (red) lines show kidney detection status (0:not detected, 1:detected). The dashed (green) lines show the visibility portions, and the solid (blue) lines display errors (top graphs in pixel, and bottom graphs in degrees).

estimation stays less than 5px for translation parameters in the ranges of $\Delta t_x \in [-70px, 69px]$, $\Delta t_y \in [-50px, 40px]$, and $\Delta t_z \in [-45px, 55px]$. For orientation parameters, the best estimation is obtained for $\Delta \theta_z$. For the parameter $\Delta \theta_y$, the proposed method provides better estimations for negative angles than positive angles. The performance of the proposed method for estimating $\Delta \theta_y$ is not satisfactory. Figure 10 shows 2D slices of six simulated ultrasound images of the RUQ view, indicating that their organ’s shapes are correctly detected.

G. Analysis of Computational Cost

The success of the proposed system highly relies on the real-time interaction between an operator (i.e. paramedic) and the portable solution. A desired computational time of the whole processing pipeline of the proposed computer-assisted probe placement solution is a few seconds. The computational time of the proposed solution is analyzed using the evaluation set including the with-kidney and without-kidney images. The computational time analysis of the proposed solution in whole and its parts, as described in II-D, is shown as a box-plot representation in Fig 11. Accordingly, the registration part has the largest computational time, $8.21 \pm 2.28$ (sec), even though it is implemented by the multi-threaded programming. Also, the computational time variation of the registration part is higher than the other parts because the number of iterations that the registration process takes to converge varies among different images. The mean and standard deviation of the overall computational time is $\mu=12.37$ (sec) and $\sigma=2.84$ (sec).

Fig. 11: Displaying computational times in seconds of the proposed solution’s parts.

which is marginally acceptable for the real-time operation. The computational time of the registration part can be reduced by combining the “parfor” and “gpuArray”, which is attainable by assigning each GPU-core to a single thread in the parfor loop [39].

IV. DISCUSSION

In this paper, a computer-assisted solution is introduced to guide paramedics to find a correct ultrasound probe placement to scan an abdominal organ of interest. Compared to the existing solutions, the proposed solution of this paper only relies on processing acquired 3D ultrasound images from
the ultrasound imaging device, without obtaining help from a remote expert or fusing extra information of positioning sensors or another imaging modality. This feature is essential for training, where the solution must be affordable, easy to use, and free of requiring an additional setup time. However, the task of processing 3D ultrasound images faces many challenges (Sec. I), and a reliable solution is only achievable by thoroughly addressing the ultrasound challenges. In the proposed solution of this paper, an organ-specific preprocessing is represented to enhance 3D ultrasound images for each organ of interest, while minimizing the computational time for real-time triaging. To register an organ’s shape model on an input image data, we represented a new registration method based on the RCC metric to obtain robustness and reliability against organ’s shape occlusion.

The performance and utility of the proposed solution is demonstrated using the case study on the RUQ view, where the right kidney is visualized and selected as the organ of interest. The RUQ view is chosen since it has a paramount importance for triaging abdominal trauma patients. The first experiment is derived using actual 3D ultrasound images of the RUQ view, acquired from both healthy volunteers and unhealthy subjects, aiming to validate the accuracy of the proposed organ’s detection for actual images. Since the proposed RCC metric is robust against organ’s shape deformation and occlusion, the proposed method has demonstrated better kidney detection results compared to the state-of-the-art in Table II. In ultrasound images of trauma patients, the right kidney shape and its surrounding region are morphologically changed in 3D ultrasound images, due to the presence of internal fluids near the right kidney. Therefore, the reported results of the unhealthy subjects reflect the robustness of the methods against organ’s shape distortion. According to Table II, the proposed method of this paper has obtained the highest accuracy and sensitivity of detecting the kidney shape in the images of trauma patients.

In the calculations of detection accuracy, sensitivity, and specificity, we only consider the detected center points are placed within an acceptable distance from the actual center points, however, these measures do not reflect the accuracy of detecting the center points, with respect to the actual center points. We calculated the Euclidean distance error of detected center points, with respect to their corresponding actual center points, of the kidney shape in the with-kidney 3D ultrasound images, as another key parameter to evaluate and compare the performance of the proposed method of this paper against the other methods. The reported results of the Euclidean distance errors of the methods and the performed statistical analysis indicate that the proposed method of this paper significantly performs better compared to the other methods, in terms of the accuracy of detecting center points of the kidney shape in 3D ultrasound images.

In the second experiment, the robustness of the proposed organ’s shape detection and localization toward organ’s shape deformation and occlusion is evaluated. Because the actual 3D ultrasound images do not provide enough flexibility and variability to evaluate the robustness toward organ’s shape occlusion and deformation, even by increasing the number of actual images, we developed and used a 3D ultrasound image simulator that mimicked actual images of the RUQ view with the desired organ’s shape deformation and occlusion. The reported results in Fig. 9 reveal that the proposed method provides an accurate estimation of the organ’s shape translations. We observed that the signs of estimated orientations are always correct for angles greater than 10 degrees. Thus, to correct a probe orientation over $x$, $y$, and $z$ axes, we send step-wise commands to paramedics to rotate the probe about 10 degrees in clockwise or counter-clockwise directions.

The computational time of the proposed method has a vital importance for the proposed solution to be successfully applied in emergency healthcare. Since the proposed solution is under development, it has been developed in MATLAB, which simplifies and accelerates the entire process of assessing a concept idea from its design through its evaluation. However, the overhead computational load might de-emphasize the utility of the proposed solution in the real-time interaction with an operator. To minimize the computational time, the proposed method has been developed by considering the following tricks: 1) avoiding the use of nested loops, 2) using built-in MATLAB functions, 3) utilizing GPU-powered MATLAB functions to perform highly parallelizable/ non-complicated computations, and 4) using multi-threading multi-core capability of MATLAB to speed up complicated computations (i.e., the proposed registration method). The reported computational times of the entire processing pipeline and the parts of the proposed solution indicate that the proposed solution has the potentials to be used in real-time operations, though, it needs more efforts to reduce the current computational time. The proposed solution can be run on portable workstations supporting Intel-Xeon mobile processors and NVIDIA Quadro graphic processors.

V. Conclusion

In this paper, we introduced a new solution to provide computer-assisted ultrasound probe placement for imaging abdominal organs without obtaining help from a remote expert. The proposed solution consists of two phases, including initial probe placement, and correcting probe placement. In the first phase, anatomical knowledge of the abdominal organ’s location is fed into the imaging process to guide a paramedic to put the ultrasound probe on an initial placement that provides at least a partial visualization of an organ of interest. In the second phase, anatomical knowledge of the abdominal organ’s shape is fed into the imaging process to fine-tune the ultrasonic probe placement to acquire a correct view of an organ of interest. We introduced an implicit representation to generate a shape model for each organ of interest based on anatomical knowledge of the organ’s shape and statistical representation of the organ’s shape variability. As a contribution of this paper, we represented an organ-specific preprocessing method to enhance input images. To detect an organ’s shape in a 3D ultrasound image, the shape model is registered on the enhanced images. We introduced the regularized cross-correlation metric to provide a robust registration against organ’s shape occlusion. We performed two experiments, using
actual and simulated ultrasound images of the RUQ view, to
evaluate the accuracy and robustness of the proposed method
in the presence of abnormalities and organ’s shape deformation
and occlusion. In future works of the proposed solution, we
will attempt to improve the accuracy of estimating orientation
parameters, will try to use texture information of an organ of
interest to improve detection and localization accuracy.

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