CONTINUOUS INFERIOR VENA CAVA DIAMETER TRACKING THROUGH AN ITERATIVE KANADE–LUCAS–TOMASI-BASED ALGORITHM

BARRY BELMONT,* ROSS KESSLER,†‡ NIKHIL THEYYUNNI,†‡ CHRISTOPHER FUNG,† ROBERT HUANG,† MICHAEL COVER,‡ KEVIN R. WARD,†‡ ALBERT J SHIH,*‡ and MOHAMAD TIBA†‡

*Department of Biomedical Engineering, University of Michigan, Ann Arbor, Michigan, USA; †Department of Emergency Medicine, University of Michigan, Ann Arbor, Michigan, USA; and ‡Michigan Center for Integrative Research in Critical Care (MCIRCC), University of Michigan, Ann Arbor, Michigan, USA

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Abstract—Ultrasound assessment of the respiratory-induced change in size of the inferior vena cava is a useful technique in the evaluation and management of critically ill patients. We have developed an automated technique based on the Kanade–Lucas–Tomasi feature tracker and pyramidal segmentation to continuously track the diameter of the inferior vena cava during ultrasound. To test the accuracy of this automated process, the inferior vena cava of 47 spontaneously breathing patients were measured by trained ultrasound physicians and compared against the results obtained via the automated tracking. Good agreement between the techniques was found, with intra-class correlation coefficients for maximum vessel diameter, minimum diameter and caval index of 0.897, 0.967 and 0.975, respectively. More than 95% of the difference between physicians and automated measurements agreed to within 10% of the inferior vena cava collapse. Furthermore a phenomenon of cardiac collapsibility index variability was observed and reported. The accuracy and precision of this algorithmic technique provide a foundation for future automated measures for critical care ultrasound. (E-mail: rokessle@med.umich.edu) © 2018 World Federation for Ultrasound in Medicine & Biology. All rights reserved.

Key Words: Inferior vena cava, Fluid responsiveness, Feature tracker, Cardiac collapsibility index.

INTRODUCTION

Ultrasound measurement of respiratory-induced change in inferior vena cava (IVC) diameter has been reported to be a non-invasive guide to fluid therapy (Brennan et al. 2007). In critical care, predicting fluid responsiveness is particularly challenging, but respiratory variation of the IVC diameter has been found to be predictive in certain patient populations (Barbier et al. 2004; Dipti et al. 2012; Feissel et al. 2004; Ferrada et al. 2012). Such a measurement can be acquired at bedside with point-of-care ultrasound (Fig. 1).

In mechanically ventilated patients breathing passively on the ventilator, the IVC will distend as intrathoracic pressure increases and decreases venous return during a positive-pressure breath. An increase in IVC diameter with inspiration above a threshold is associated with fluid responsiveness (Barbier et al. 2004; Feissel et al. 2004). In spontaneously breathing patients this relationship is reversed—with inspiration there is a decrease in intrathoracic pressure and increased venous return. This leads to a collapse in IVC diameter during inspiration. The situation is more complicated in a mechanically ventilated patient who is making significant respiratory effort, and IVC collapse or distension may be seen, depending on the degree of respiratory effort. The significance of IVC diameter in this situation is not well studied.

The diagnostic accuracy of IVC collapsibility for identifying fluid responsiveness in spontaneously breathing patients has been re-evaluated and called into question (Muller et al. 2012). Of note, Muller et al. suggested that the high degree of cycle-to-cycle variability with respiration limited the use of IVC collapsibility. An automated method for continuously tracking IVC diameter would not only provide clinicians with an additional tool in the management of critically ill patients, but it would also facilitate multiple, consistent measurements to account for cycle-to-cycle variability in spontaneously breathing patients.
There are several limitations to clinician-based measurements of the IVC. Careful measurement, which can include serial measurements performed over time, requires both additional time at the bedside and consistent measurement in the same location along the IVC. In addition, clinicians often use a rough estimate of IVC diameter and collapse rather than true, consistent measurements, and no tool is currently available that can measure the diameter of the IVC continuously during the performance of the ultrasound.

To provide such a tool, we developed a simple point-tracking algorithm based on the paired combination of the Kanade–Lucas–Tomasi feature tracker and pyramidal segmentation. Working with ultrasound videos in the DICOM (Digital Imaging and Communications in Medicine) standard, this simple algorithm allows a clinician to manually select points on either side of the vessel to track over the course of the video. The distance between these two points is then calculated, and the respiratory variations in the diameter of the IVC can be calculated for the caval index. With this technique, we have created a tool to investigate the continuous waveform of the IVC diameter, opening many avenues for future research, including the recently reported cardiac collapsibility index (Sonoo et al. 2015). In the data presented in this article, the algorithm identifies the maximum and minimum IVC diameters over the course of the video. To begin tracking, a pair of points on the vessel’s edge are selected on an initial image. The two points are selected independently as follows. Let \(I_1(x, y)\) be the pixel intensity value of \(I_1\) at a point, \([x, y]^T\). Let \(\mathbf{u} = [u_x, u_y]^T\) be a point on the first image, \(I_1\). The goal is to find a point \(v\) on \(I_2\) where \(I_1(\mathbf{u})\) and \(I_2(\mathbf{v})\) are most similar, with the assumption that the feature located at \(I_1(\mathbf{u})\) has moved to \(I_2(\mathbf{v})\) by a motion vector \(\mathbf{d} = [d_x, d_y]^T\). To establish the frame-to-frame motion vector, \(\mathbf{d}\), we will seek to minimize a residual function, a sum of squared differences, defined as

\[
\epsilon(\mathbf{d}) = \epsilon(d_x, d_y) = \sum_{x=I_1-x-W_x}^{I_1+x+W_x} \sum_{y=I_1-y-W_y}^{I_1+y+W_y} (I_1(x, y) - I_2(x + d_x, y + d_y))^2
\]

(1)

**METHODS**

**Algorithm description**

Our algorithm makes use of two techniques, the Kanade–Lucas–Tomasi (KLT) feature tracker and pyramidal segmentation, and is administered in MATLAB. The KLT feature tracker is a technique commonly used in computer vision to follow certain image features (edges, points, etc.) from one frame to the next. Traditional image-tracking techniques can be computationally costly as they try to match a subset of pixels of interest (known as a kernel) from one frame to within another, larger subset of pixels (known as a search window) in a frame that follows. There are many techniques to perform this action with varying costs of computation. To mitigate these computational costs, the KLT technique makes use of spatial intensity information to direct the search for the motion vector that best describes the feature’s change in position from one frame to the next.

One of the limitations of the KLT tracker is that the motion vector must be small. That is, the KLT technique alone is not capable of measuring large changes in position. To work around this problem, our algorithm employs a pyramidal segmentation technique to subsample an image—reducing its resolution and increasing the spatial information inherent in each pixel—to perform large motion tracking, then feeding the results of the low-resolution tracked images to higher-resolution images. In this way the accuracy and speed of the KLT technique can be used to track a feature, in this case the walls of the IVC, over large distances.

To begin tracking, a pair of points on the vessel’s edge are selected on an initial image. The two points are tracked independently as follows. Let \(I_1\) and \(I_2\) be two gray-scaled images in sequence. \(I_i(x, y)\) is the pixel intensity value of \(I_i\) at a point, \([x, y]^T\). Let \(\mathbf{u} = [u_x, u_y]^T\) be a point on the first image, \(I_1\). The goal is to find a point \(v\) on \(I_2\) where \(I_1(\mathbf{u})\) and \(I_2(\mathbf{v})\) are most similar, with the assumption that the feature located at \(I_1(\mathbf{u})\) has moved to \(I_2(\mathbf{v})\) by a motion vector \(\mathbf{d} = [d_x, d_y]^T\). To establish the frame-to-frame motion vector, \(\mathbf{d}\), we will seek to minimize a residual function, a sum of squared differences, defined as

\[
\epsilon(\mathbf{d}) = \epsilon(d_x, d_y) = \sum_{x=I_1-x-W_x}^{I_1+x+W_x} \sum_{y=I_1-y-W_y}^{I_1+y+W_y} (I_1(x, y) - I_2(x + d_x, y + d_y))^2
\]
where $\epsilon(d)$ is the residual error, and $w_x$ and $w_y$ are the integration window size parameters (with a window size equal to $(2w_x+1) \times (2w_y+1)$, centered $[x \ y]^T$). If we then set the derivative of the matching error with respect to the displacement vector to 0, the error minimizing displacement vector can be found:

$$\frac{\partial \epsilon(d)}{\partial d} = 0$$

$$= -2 \sum_{x = u_x - w_x}^{u_x + w_x} \sum_{y = u_y - w_y}^{u_y + w_y} (I_1(x,y) - I_2(x + d_x, y + d_y)) \begin{bmatrix} \frac{\partial I_2}{\partial x} \\ \frac{\partial I_2}{\partial y} \end{bmatrix}$$

$$= \mathbf{b}$$

Simplifying eqn (2) by substituting the first-order Taylor series expansion of $I_2(x + d_v,y + d_v)$ gives

$$\frac{\partial \epsilon(d)}{\partial d} \approx -2 \sum_{x = u_x - w_x}^{u_x + w_x} \sum_{y = u_y - w_y}^{u_y + w_y} (I_1(x,y) - I_2(x,y))$$

$$- \mathbf{d} \begin{bmatrix} \frac{\partial I_2}{\partial x} \\ \frac{\partial I_2}{\partial y} \end{bmatrix} \begin{bmatrix} \frac{\partial I_2}{\partial x} \\ \frac{\partial I_2}{\partial y} \end{bmatrix}$$

$$= \begin{bmatrix} I_x & I_y \end{bmatrix} \begin{bmatrix} I_x & I_y \end{bmatrix}^T$$

From here we can define the frame-to-frame difference at the point of interest as

$$\delta I(x,y) = I_1(x,y) - I_2(x,y)$$

and the image gradient as

$$\nabla I = \begin{bmatrix} I_x \\ I_y \end{bmatrix} = \begin{bmatrix} \frac{\partial I_2}{\partial x} \\ \frac{\partial I_2}{\partial y} \end{bmatrix}$$

where

$$I_x(x,y) = \frac{\partial I_1(x,y)}{\partial x} = \frac{I_1(x + 1,y) - I_1(x - 1,y)}{2}$$

$$I_y(x,y) = \frac{\partial I_1(x,y)}{\partial y} = \frac{I_1(x,y + 1) - I_1(x,y - 1)}{2}$$

Substituting these into eqn (3) yields

$$\frac{\partial \epsilon(d)}{\partial d} \approx \sum_{x = u_x - w_x}^{u_x + w_x} \sum_{y = u_y - w_y}^{u_y + w_y} (d^T \nabla I - \delta I) \nabla I^T$$

Combining terms and transposing create

$$\frac{1}{2} \begin{bmatrix} \frac{\partial \epsilon(d)}{\partial d} \end{bmatrix}^T \approx \sum_{x = u_x - w_x}^{u_x + w_x} \sum_{y = u_y - w_y}^{u_y + w_y} \left( \mathbf{d}^T \begin{bmatrix} I_x \\ I_y \end{bmatrix} I_1 \begin{bmatrix} I_x & I_y \end{bmatrix} - \begin{bmatrix} \delta I_x \\ \delta I_y \end{bmatrix} \right)$$

Defining matrix $G$ as a Harris matrix and $b$ as a metric of feature frame-to-frame difference as

$$G = \sum_{x = u_x - w_x}^{u_x + w_x} \sum_{y = u_y - w_y}^{u_y + w_y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

$$\mathbf{b} = \sum_{x = u_x - w_x}^{u_x + w_x} \sum_{y = u_y - w_y}^{u_y + w_y} \begin{bmatrix} \delta I_x \\ \delta I_y \end{bmatrix}$$

respectively, yields a final form of

$$\mathbf{d}_{opt} = G^{-1} \mathbf{b}$$

where $\mathbf{d}_{opt}$ is that displacement vector that causes the derivative of the residual function to be equal to zero. Thus, by calculating the intensity gradients, the optimal displacement vector can be found *via* the KLT technique. However, because the matrix $G$ must be invertible and because of the limitations inherent in the first-order Taylor series approximation, the pixel displacements that are possible to measure must be small.

One means of measuring both the computational efficiency and the spatial distance that is possible to measure is to subsample an image. One such technique that is able to consistently subsample an image repeatedly and feed information forward and backward from lower-resolution to higher-resolution images is pyramidal segmentation. Starting with an image of resolution $W \times H$ at a level $L_0$, an image pyramid is built by subsampling a smoothed image by a factor of 2 along each coordinate direction at each level. Thus, the size of the image at $L_1$ would be $W/2 \times H/2$, at $L_2$ it would be $W/4 \times H/4$ and so on.

Figure 2 illustrates this process.

Given a point $u$ in $I_1$, we want to find its corresponding location in $I_2$ at $v = u + d$. The corresponding point of $u(u^0)$ on the pyramidal image $I^0$ is $u^L$ and is defined as

$$u^L = \frac{u}{2^L}$$

An initial $d^{L_m}$ is computed at the uppermost pyramid level, $L_m$, by minimizing its level-specific residual function. The final value of $d^{L_m}$ is then passed as the initial guess for $d^{L_{m-1}}$ down to the next pyramidal image level, $L_{m-1}$, to find a value of $d^{L_{m-1}}$ that minimizes its level-specific residual function. This process is continued until the final maximal resolution image at level $L_0$ is reached, from which a final motion vector, $d = d^0$ is calculated.

Setting $g^L = [g_x^L, g_y^L]^T$ as an initial guess at level $L$ (valid for levels $L_1$ to $L_m$), the algorithm seeks to find the pixel displacement vector $d^L = [d_x^L, d_y^L]^T$ that minimizes the pyramidal residual error function.
Starting from the highest pyramidal level, \( L_m \), a guess is initialized as \( \mathbf{g}^{L_m} \), and from this guess, an initial motion vector, \( \mathbf{d}^{L_m} \) is calculated. The initial guess and calculated motion are then fed down the pyramid to level \( L_{m-1} \) by the function

\[
\mathbf{g}^{L_{m-1}} = 2(\mathbf{g}^{L_m} + \mathbf{d}^{L_m})
\]

Iterating the above function down each level of the pyramidal image yields a final displacement vector

\[
\mathbf{d} = \sum_{n=0}^{m} 2^n \mathbf{d}^{L_n}
\]

At every level, the goal is to find the displacement vector that minimizes the matching function. However, rather than search through every possible pixel in an image, a significant computational undertaking for even the smallest and shortest of video clips, one may use the functional relationship between the matching error, \( \epsilon(\mathbf{d}) \), and the displacement vector, \( \mathbf{d} \), to find the optimal displacement vector via the KLT technique at each pyramidal level quickly then passing the information down to the next level.

This algorithm is particularly robust in this use case because of the textured patterns caused by the specular reflections from the ultrasound imaging process (allowing unique gray patterns to arise) and the walls’ easy demarcation from blood (which tends to appear black in ultrasound images). Our implementation of the algorithm uses, on average, less than 20 s to process one cine loop.

**Experimental design**

Fifty spontaneously breathing patients receiving hemodialysis had their IVCs examined while in a supine position. Informed consent was obtained from each participant in the study, and the University of Michigan institutional review board approved the study. A physician with training in ultrasound imaged the IVC subcostally in a longitudinal view using a phased array or curvilinear ultrasound transducer. Ultrasound was performed using a commercially available device (Mindray M7, Mindray North American, Mahwah, NJ, USA). A total of 64 B-mode cine loops 10–15 s in length over the course of respiration were saved in the DICOM format for post-clinical evaluation. Though many sonologists have used M-mode imaging to calculate IVC collapsibility and distensibility, our observations and the observations of others have indicated that respiration results in caudal displacement of the IVC, often leading to inaccurate M-mode-based measurements (Blehar et al. 2012; Wallace et al. 2010).

Two trained ultrasound physicians then independently measured the caval index by identifying the image frame of minimum and maximum IVC diameter during a cine clip at approximately 2 cm caudal to the hepatic vein inlet. The caval index, CI, for spontaneous breathing was defined as the difference between the maximum, \( D_{\text{max}} \), and minimum, \( D_{\text{min}} \), diameters normalized to the maximum diameter, represented as a percentage:

\[
CI = \frac{D_{\text{max}} - D_{\text{min}}}{D_{\text{max}}} \times 100 \%
\]

A wide variety of inferior vena cava cine clips (Fig. 3) were measured to test the limitations of the automated measurement. Using the same image frame of the minimum and maximum IVC diameter at approximately 2 cm caudal to the hepatic vein inlet, points were selected by a researcher that were then tracked frame-to-frame via the algorithm described in the previous section. The minimum and maximum points within a clip
Fig. 3. Varieties of inferior vena cava images. A point-tracking system must be robust enough to handle the substantial variety of ultrasound images that arise from patients.
were detected via peak detection, and the caval index for each clip was calculated. The results obtained from the clinicians and the software were compared.

Statistical analysis

Descriptive statistics, including means, standard deviations and diagrams, were found to visually inspect the data. Intra-class correlation coefficients were calculated to determine the level of agreement and consistency between the physician and automated measurements. The method described by Bland and Altman was used to analyze the bias and precision between automated and physician measurements and to determine the limits of agreement by defining the mean and standard deviation (SD) of the differences. The limits of agreement were defined as the mean difference 2(SD) of the differences. Data are presented as the mean (SD), and where appropriate, 95% confidence intervals are reported. For all calculations, p values < 0.05 were considered to indicate statistical significance. MATLAB was used for all data analysis.

RESULTS

Of the 64 initial cine clips, 3 could not be measured by the clinicians (lacking the necessary anatomic landmark). An additional 4 could not be measured by the algorithm because of software crashes across many versions of MATLAB. Therefore, a total of 57 cine clips from 47 patients were included for analysis.

Figures 4 (a, b) illustrate the distribution of maximum IVC diameters and caval indices observed by the trained physicians in this study. The maximum diameters tend to fit a normal distribution centered around a mean of 17.9 mm with a standard deviation of 4.12 mm. The caval indices as measured by the physicians varied widely from 0 to 100%, with a predominant peak between 10% and 30%. Thirty-two patients (40 cine clips) had an IVC collapse of <50%, and 15 patients (17 cine clips) had a collapse of >50%.

Figure 5 is a plot of the means of and differences between the automated and physician measurements of the caval indices. The difference was found by subtracting the automated measurement from the physician measurement. Three outliers were observed at higher levels of collapse, indicating certain limitations of the automated technique at higher caval indices. When these outliers are excluded, the average measured difference between the two techniques is 2.12%, with a standard deviation of 4.48%. More broadly, there is good agreement between the two types of measurement to within 10% for more than 95% of the data.

Table 1 lists the averages, standard deviations and ranges for the maximum IVC diameter, minimum IVC diameter and caval indices from both the physician and algorithmic measurements. Intra-class correlation coefficients of the form ICC(2,1) from Shrout and Fleiss (1979) were calculated for the maximum diameter, minimum diameter and caval index, yielding values of 0.897, 0.967 and 0.975, respectively. All measured data, including the three identified outliers, were used to populate this table.

One result observed through the automated measurement that is difficult to discern manually by a clinician is diameter changes corresponding to both respiratory and cardiac cycles. Figure 6 illustrates the effects of both cycles in a spontaneously breathing subject. The raw signal in Figure 6(a) is the result straight from the algorithm described. The IVC collapsibility indices presented were based on this raw signal. However, to isolate the respiratory signal, this raw signal was low-pass filtered with a corner frequency of 0.6 Hz. Subtracting the respiratory signal from the raw signal resulted in what we deem the cardiac signal seen in Figure 6(b). Only recently have researchers begun to explore the potentially useful metric of the cardiac collapsibility index (CCI) in the IVC (Sonoo et al. 2015). To our knowledge, no researchers have previously presented evidence of the existence of CCI variability, as illustrated in Figure 6(b).

DISCUSSION

Our algorithmic approach to measuring the IVC diameter accurately replicates the maximum, minimum and collapsibility to within 10% of physician-reported values in >95% of measured cases, with intra-class correlation coefficients for each of the parameters equal to 0.897, 0.967 and 0.975, respectively. Such a high degree of agreement indicates that our feature-tracking algorithm produces measurements functionally equivalent to those made by trained physicians. The vast majority of the differences between the measurements from a physician and from the algorithm are <1 mm, stemming from a slightly different set of points measured along or at the edge of the vessel. This degree of accuracy and precision, coupled with the ability to give high-quality continuous tracings of the IVC, provides strong evidence for using this technique for future work.

Limitations to the proposed algorithm do, however, exist. The feature to be tracked, the edge of the vessel, must be clear and consistent. The algorithm as developed and reported has no means by which to correct for cylinder tangent effects (when the scan plane travels through an off-center portion of the IVC), highly noisy images or ultrasonic shadows, as may appear if imaging between ribs. Another possible source of error in the measurement comes from very
Fig. 4. A histogram of (a) the maximum diameters of the IVCs as measured by the clinicians and (b) the caval index of the IVCs as measured by the clinicians. IVC = inferior vena cava.

Table 1. Averages, standard deviations, ranges and ICCs for the maximum IVC diameter, minimum IVC diameter and caval index as measured by physicians and the proposed algorithm

<table>
<thead>
<tr>
<th></th>
<th>Maximum diameter (mm)</th>
<th>Minimum diameter (mm)</th>
<th>Caval index (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physician</td>
<td>17.9</td>
<td>12.1</td>
<td>36.4</td>
</tr>
<tr>
<td>Algorithm</td>
<td>18.6</td>
<td>13.1</td>
<td>33.5</td>
</tr>
<tr>
<td><strong>Standard deviation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physician</td>
<td>4.12</td>
<td>6.67</td>
<td>29.2</td>
</tr>
<tr>
<td>Algorithm</td>
<td>4.88</td>
<td>6.85</td>
<td>26.0</td>
</tr>
<tr>
<td><strong>Range</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physician</td>
<td>18.7</td>
<td>24.2</td>
<td>100</td>
</tr>
<tr>
<td>Algorithm</td>
<td>20.2</td>
<td>25.1</td>
<td>84.1</td>
</tr>
<tr>
<td><strong>ICC [95% CI]</strong></td>
<td><strong>0.897 [0.817, 0.941]</strong></td>
<td><strong>0.967 [0.881, 0.986]</strong></td>
<td><strong>0.975 [0.942, 0.988]</strong></td>
</tr>
</tbody>
</table>

CI = confidence interval; ICC = intra-class correlation coefficient.
Fig. 5. Bland–Altman plot of the caval indices as measured by physicians and the algorithm. The three white points at high levels of collapse represent outliers in the data set.

Fig. 6. Continuous tracking of the inferior vena cava diameter with respect to time. (a) The raw tracked diameter can be seen to be composed of both a respiratory signal and a cardiac signal. (b) Respiratory-induced variations in the cardiac signal also exist, with maximal variations occurring during inspiration. IVC = inferior vena cava.
large, sudden movements as may accompany a forceful sniff. Though pyramidal segmentation has been employed to combat these effects, caution is advised before implementing this algorithm to investigate very large and rapidly occurring IVC collapse. In its current form, the algorithm does not detect whether the maximum and minimum detected in the clip correlate with an IVC collapse from negative-pressure inspiration or IVC distension from positive-pressure inspiration. Similarly, the algorithm has no way currently to detect respiratory maneuvers such as breath holds, heavy breathing, sniffs and Valsalva maneuvers.

Our algorithm can facilitate multiple, consistent measurements to account for cycle-to-cycle variability in spontaneously breathing patients, as well as identification of more subtle features within each respiratory cycle. Further work is needed to automate detection of modes of breathing and/or respiratory maneuvers. However, we feel that with a continuous tracing of IVC diameter over time, this is a feasible extension of this algorithm. Of particular interest is the potential physiologic meaning of both the CCI and CCI variability. These may represent new diagnostic and therapeutic targets. However, it will be necessary to clearly track these in real time to better understand their importance, and to this end, the algorithm described in this article may help. We are currently investigating these parameters and their change in response to both positive and negative fluid challenges in spontaneous and mechanically ventilated patients.

**CONCLUSION**

We have reported the feasibility of using an image processing tool to continuously measure IVC diameter as more accurate and more rapid than measurements made by a trained sonographer. This tool provides unprecedented access to variability and subtle changes in the respiratory cycle and the underlying cardiac cycle-related signals within the IVC. The accuracy and precision of this algorithmic technique provide a foundation for future automated measures for critical care ultrasound.

Conflict of interest disclosure—The authors have no conflicts of interest.

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