Int J CARS (2015) 10:1963–1971
DOI 10.1007/s11548-015-1214-1

ORIGINAL ARTICLE

Deep venous thrombosis identification from analysis of ultrasound data

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Received: 14 February 2015 / Accepted: 15 April 2015 / Published online: 16 May 2015

Abstract
Purpose The purpose of this research was to determine whether combined ultrasound- and sensor-based compressibility and augmented blood flow measures yielded better results for DVT detection than for the individual measures alone.
Methods Twenty-six limbs from 19 patients were scanned using a sensorized ultrasound DVT screening system, and compressibility and flow measures were obtained at 125 locations. Results from conventional compression ultrasound examination were used as gold standard, with seven vessels (four patients) positive for DVT. A classification approach was used to combine the individual DVT measures per vessel and generate an optimal feature for every possible combination of individual measures. Sensitivity and specificity were calculated for the individual measures and for all combined measures, as was a usefulness criteria J for measuring class separability.
Results Seven optimal combined features were found with 100 % sensitivity and 100 % specificity, with the best combined feature having a J value over two orders of magnitude greater than the best individual DVT measure.
Conclusions The proposed approach for DVT detection combines different aspects of thrombus detection in a novel way generating a quantifiable measure and outperforms any of the individual measures when used independently. All of the combined measures included the flow measure as well as the slope compressibility measure, which uses the magnitude of the force applied by the ultrasound probe, suggesting that these measurements provide important information when characterizing DVT.

Keywords Deep venous thrombosis · Sensorized screening system · Classification · Ultrasound

Introduction

The quick and accurate detection of deep venous thrombosis (DVT) is of extreme importance during postsurgical care, particularly after procedures such as hip and knee replacements. This disease, where clots form in the lower limbs and can obstruct blood flow, is a precursor to the potentially deadly pulmonary embolism (PE). Approximately 80 % of the emboli to the lungs arise from thrombi in the leg veins [1], and estimates of deaths each year because of PE are 150,000–200,000 in the USA [2].

It has been suggested that by controlling and preventing DVT, the prevention of PE can be achieved [3]. If DVT can be detected in its early stages, for example, through the practice of screening patients postoperatively, the occurrences of major PE can be reduced because of earlier diagnosis and

The authors gratefully acknowledge MITACS, a Network of Centres of Excellence, PRECARN and NSERC for providing funding for this research.

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treatment of DVT [4]. In this setting, a fast, simple and reliable test that could be carried out directly where the patients are located would be extremely useful [5].

An ultrasound-based screening system for DVT that uses contour detection and measurements from a sensorized probe to determine vessel compressibility, and therefore the possibility of DVT, has been previously presented [6]. Transverse vessel contours are detected in B-mode ultrasound images using a spatial Kalman filter with an ellipse model [7], and vessel location is tracked in real time using sensor- and image-based measurements. The system has undergone laboratory and clinical evaluations [8] with encouraging results. Sensitivity of up to 100 % for DVT detection using the vessel compressibility measures has been reported for this system in a previous clinical evaluation [14].

This paper builds on previous work toward the development of an accurate and reliable DVT screening system, using measures calculated from ultrasound data. A classification approach was used to evaluate the usefulness of a series of DVT measures and also as the basis for calculating a single optimal measure by combining the various criteria. Patient data, collected after Institutional Clinical Ethics Board Review at the Orthopedics ward of the University of British Columbia Hospital, were used to evaluate the new objective measures and the optimal feature calculation.

Vessel assessment criteria

Determining vessel compressibility by observing the transverse area of the veins using B-mode ultrasound when gentle pressure is applied has long been recognized as the most accurate and useful criterion for DVT diagnosis [9]. Loss of compressibility of a thrombus filled vein under gentle probe pressure, i.e., compression ultrasound (CUS) [10], accurately indicates high probability of anechoic thrombosis. On the contrary, if a vein does completely collapse, the possibility of DVT in that section of the vein is very small. In addition to vessel compressibility, determining whether blood flow is unobstructed in a vessel can help confirm or rule out the possibility of DVT.

Compressibility criteria

Two compressibility criteria based on CUS and aimed at quantifying vessel stiffness and the probability of DVT within the examined vessel were presented by Guerrero et al. [6].

The first measure, the transverse area ratio (TAR), is defined as the ratio of the minimum ($A_{\min}$) to the maximum ($A_{\max}$) transverse vessel areas for a specific segment, or

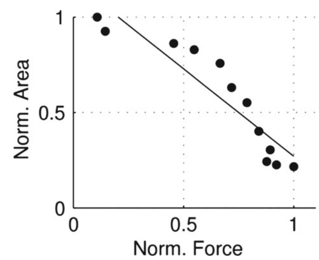

Fig. 1 Typical data for a healthy, compressible vein

$$\mathrm{TAR} = A_{\min}/A_{\max} \tag{1}$$

The TAR indicates how much the vessel area decreases under compression, as a percentage of the original transverse vessel area. A large TAR (∼100 %) indicates an incompressible vein segment and the possibility of DVT, while a small TAR (∼0 %) indicates a normal compressible vein.

The second measure, called the *slope* measure, is a *vessel stiffness*, which maps normalized transverse vessel area (**A**) measurements to normalized applied force (**F**) measurements obtained from the ultrasound probe during compression. The vessel stiffness measure is the slope m of the fitted line

$$\mathbf{A} = m\mathbf{F} + b \tag{2}$$

where the A-axis intercept b is not used. A slope value $m \sim 0$ indicates venous incompressibility and possible DVT, while a healthy vein would generate an $m \sim -1$. The normalization of F and A is performed based on the maximum measurement values at a given location. The slope measure is represented by the line in Fig. 1, while the TAR would be the ratio of the minimum to maximum of the data points.

In the DVT screening system, the vessels of interest are imaged on a transverse plane and the user gently presses down with the ultrasound probe and releases, cued by the system. A sensorized ultrasound probe (see Fig. 3) is used to measure the applied force while an examiner performs a modified CUS examination. An electromagnetic sensor provides the location information used to register the data.

The transverse vessel areas are estimated using a contour detection algorithm that uses a spatial Kalman filter and an ellipse model [7]. This radial search algorithm detects the vessel walls and generates an estimate of the ellipse parameters of the model using the framework of the extended Kalman filter. In addition, the system constructs a 3D model of the scanned vessel using the uncompressed vessel contours (Fig. 2). The contour detection has an error of 1.06–1.70 pixels when segmenting patient images, and the area estimation has a mean error of about 10 %. These errors are approximately equal to inter-observer variation obtained from expert segmentation of the same images [7]; we therefore believe

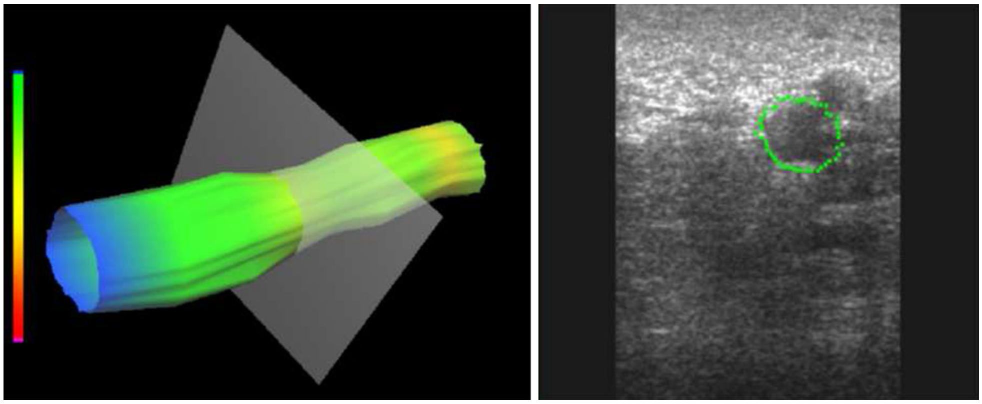

Fig. 2 A scanned vessel model (*left*), with results of a compression examination *color-mapped* to the surface to indicate vessel compressibility. B-mode ultrasound with detected vessel contour (*right*)

that the accuracy of the detection algorithm does not significantly affect the results.

Validation of compressibility criteria

The compressibility criteria have been validated in previous studies, when using the DVT system to obtain data from a total of 34 patients, 59 scanned vessels and 391 individual compression assessments [14]. In all cases, the results of a standard CUS examination were used as the gold standard, where patients were classified as either positive or negative for DVT. These results were compared to the data generated by applying a threshold to the compressibility criteria, where a threshold of 55 % was used for the TAR and −0.2 was used for the slope [6].

In a first study, the sensitivity obtained with the TAR measure was 92 %, while a sensitivity of 100 % was obtained with the slope measure. Specificity was in the range of 50–65 %. In a second study, the sensitivity and specificity of the system are 93 and 25 %, respectively, when using the average TAR values for each vessel model. When using the slope measure, a sensitivity of 100 % was obtained, and specificity was in the range of 36–64 %.

Flow criteria

Ultrasound can also be used to determine whether there is adequate blood flow within a vessel. In an augmentation examination, the vessel of interest is viewed on the long axis using color flow imaging, and the patient either flexes their ankle or the examiner gently squeezes the patient's calf. A large increase in flow is observed for healthy vessels, while a minimal or nonexistent flow increase points toward a vessel with DVT. In this case, the thrombus does not have to be directly imaged. However, because of low sensitivity, color flow imaging cannot stand alone as a method for DVT detection [11].

A flow ratio calculation was introduced by Sasaki et al. [12]. The peak flow signal at active maximum ankle flexion and the peak flow signal at rest were measured for 11 patients (22 limbs) with continuous wave Doppler and used to manually calculate flow ratios in the femoral veins, and care was taken to view the vessels in a longitudinal plane, with a 60° angle between the vessel and the CW Doppler direction. Flow ratios for patients with non-occlusive DVT were significantly lower than those without. Mean flow ratios for patients positive for DVT were 1.18 (range 1.0–1.3), while mean ratios for those negative for DVT were 3.31 (range 1.8–4.8).

An objective measure based on flow characterization was included in our DVT screening system based on the conventional flow augmentation examination. Continuous wave Doppler was not used, but rather the color flow imaging modality was used instead. These data were provided as a separate image stream by the system (see "DVT screening system" section). A significant number (∼500) of flow data points are acquired when the patient is at rest and a similar number of data points are acquired while actions to augment blood flow are performed. These data are acquired automatically centered at the location of the detected vessels described in "Compressibility criteria" section, or from user input. Peak flow values from each of the two sets are used to calculate a flow ratio as outlined by Sasaki et al.

Classification for DVT

Since a number of objective measures for detecting DVT can be calculated, a classification approach [13] was used to determine the usefulness of each and to calculate a single optimal feature which combines several of these objective measures into one, for a given dataset. This approach generates a combined feature based on the DVT measures that maximizes the class separability for DVT detection, based on

Fisher's linear discriminant analysis. In this case, the class separability criterion is J, as described below.

Patient data were collected and assigned to one of two classes based on the presence or absence of DVT as determined by a gold standard test, denoted by $\mathbf{X}_1$ and $\mathbf{X}_2$, respectively. A value J, which is interpreted to indicate the usefulness of a specific measure, is then calculated as [13]

$$J = \frac{\mathrm{Tr}(S_\mathrm{m})}{\mathrm{Tr}(S_\mathrm{w})} \tag{3}$$

where S_m is the mixture scatter matrix, and S_w is the within-class scatter matrix. The mixture scatter matrix S_m is defined as the covariance of all the measurements $\mathbf{X} = [\ \mathbf{X}_1\ \mathbf{X}_2\ ]^\top$ with respect to the global mean, or

$$S_\mathrm{m} = E\{(\mathbf{X} - \mu_\mathrm{o})(\mathbf{X} - \mu_\mathrm{o})^\top\} \tag{4}$$

given that μ_o is the mean of $\mathbf{X}$, and the within-class scatter matrix S_w is the weighted covariance

$$S_\mathrm{w} = \frac{N_1}{N} S_1 + \frac{N_2}{N} S_2 \tag{5}$$

where N_1, N_2 are the number of measurements for each class, $N = N_1 + N_2$ is the total number of measurements, and S_1 and S_2 are the covariances of $\mathbf{X}_1$ and $\mathbf{X}_2$, respectively. $\mathrm{Tr}(S_\mathrm{w})$ is a measure of the average variance of the features, across all classes.

A value of $J = 1$ indicates that the specific measure is only as good as chance for differentiating between the two classes. Higher values of J indicate an increasing ability to correctly differentiate whether a measurement belongs to one class or the other and arise when feature values are well clustered around their mean within each class and when the clusters of the different classes are well separated [13].

Our goal is to transform our m-dimensional feature vector, containing samples for some or all of the measures indicated in Table 1, into an l-dimensional vector ($m < l$) where our class separability criterion J is optimized. An optimal measure [13] was then calculated using

$$y = (\mu_2 - \mu_1) S_\mathrm{w}^{-1} \mathbf{X} \tag{6}$$

where μ_1 and μ_2 are the mean values of the measurements in class 1 (positive for DVT) and class 2 (negative for DVT), respectively, and $\mathbf{X}$ is a vector containing all the measurements from both classes. This resulting linear classifier is also known as Fisher's linear discriminant.

We calculated the optimal features for all possible combinations of the described DVT measures and obtained the corresponding J value for each. The resulting J values for each of the optimal measures were compared to determine whether the optimal, combined features provided additional information.

Once an optimal feature is obtained for a given combination of measures, S_m, S_w and J are recomputed. In use, a threshold would be established for y, and new samples for

Table 1 Individual measures used for DVT classification

Measure description	Label	[a]	[b]	[c]
Compound TAR criteria	TAR-1	1	Small	Max.
Compound TAR criteria	TAR-2	1	Small	Mean
Compound slope criteria	Slope-1	1	Small	Max.
Compound slope criteria	Slope-2	1	Small	Mean
Compound TAR criteria	TAR-3	Many	Small	Max.
Compound TAR criteria	TAR-4	Many	Small	Mean
Compound slope criteria	Slope-3	Many	Small	Max.
Compound slope criteria	Slope-4	Many	Small	Mean
Compound modified slope criteria (not normalized)	Slope-5	1	Small	Max.
Compound modified slope criteria (not normalized)	Slope-6	1	Small	Mean
Compound modified slope criteria (not normalized)	Slope-7	Many	Small	Max.
Compound modified slope criteria (not normalized)	Slope-8	Many	Small	Mean
Compound TAR criteria	TAR-5	1	Large	Max.
Compound TAR criteria	TAR-6	1	Large	Mean
Compound slope criteria	Slope-9	1	Large	Max.
Compound slope criteria	Slope-10	1	Large	Mean
Compound flow ratio	Flow-1	N/A	N/A	N/A

[a] Number of points used in outlier removal
[b] Distance threshold used in outlier removal
[c] Maximum or mean value of criteria used per vessel model

the compression and flow measures would be substituted in place of $\mathbf{X}$ (μ_1, μ_2 and S_{w}^{-1} remain the same). The result of Eq. (6) compared to the established threshold would determine whether DVT is present or not.

Experimental setup

DVT screening system

All data acquisition was performed using the DVT screening system developed by Guerrero [14]. With the system, vessels of interest are imaged as described in "Vessel Assessment Criteria" section, and the transverse area of the scanned vessels is estimated, and blood flow information is acquired. The system processes the collected data on-the-fly and generates compressibility and flow measures which in turn indicate the possibility of DVT.

The DVT screening system is implemented on a Ultrasonix Sonix® PC-based ultrasound machine with the Ulterius research package. It is a dual-core Intel Pentium 4 processor PC, running at 3.00 GHz with 1.0 GB of RAM, on a Microsoft Windows XP operating system. The research package allows direct access to the ultrasound data at the original resolution, which eliminates the need for video acquisition hardware and greatly increases system speed. The system directly reads other ultrasound parameter values such as gain, depth and frequency throughout a scan. Contour detection and tracking are performed at the native ultrasound frame rate (ranging from about 10 to about 40 Hz), and up to three vessels can be tracked and detected at once.

A sensorized handheld ultrasound probe consisting of a pair of nested shells and force and location sensors, as shown in Fig. 3, is used. Two aluminum shells surround a linear 9–4 MHz ultrasound probe. The inner shell is fixed to the probe, while the outer shell is connected to the inner shell through the 6 degree-of-freedom (DOF) force/torque sensor (Nano25, ATI Industrial Automation, Inc.) at the rear. The examiner can grasp and manipulate the ultrasound probe in a normal manner, and all applied forces and torques are measured. An electromagnetic sensor (PCIBird, Ascension Technology Corp.) is rigidly attached to the rear of the outer shell through a ∼135 mm plexiglas rod, and therefore, the location of the image plane (and extracted vessel contours) can be calculated using a calibrated transformation.

Fig. 3 Sensorized ultrasound probe used for data acquisition

The user interface, which has undergone a usability evaluation with satisfactory results [14], includes a virtual environment displayed at a fixed frame rate 20 Hz, the ultrasound image and control buttons. A touchscreen (Magic Touch X-Model, Keytec, Inc.) was placed over the standard Ultrasonix monitor and is used as the input device.

For each scanned vessel, a 3D model is constructed from discrete slices. Compression data are acquired and assigned to one of these discrete slices, using a distance threshold. Data are normalized based on the maximum F and A values at each slice, allowing for variations in vessel size and required compression force (e.g., for femoral vs. popliteal or calf veins). The resulting TAR and slope values are calculated online for each of the discrete locations of a compression examination. In addition, the system saves the raw data (ultrasound image, detected contour, force/torque and location measurements) to generate the individual data points used to calculate the compressibility measures. An additional set of measures was calculated based on the slope criteria, using non-normalized force values. The objective measure based on flow characterization was implemented using color flow imaging. Flow data were collected when the patients were at rest and while actions to augment blood flow were performed, using the location of the detected vessels or from user input. Peak flow values from each of the two sets were used to calculate a flow ratio as outlined in "Flow criteria" section.

Data acquisition

All data were collected at the University of British Columbia Hospital. Patients who had undergone hip replacement surgery or knee replacement surgery were invited to participate. Only those who could provide informed consent were scanned. The DVT screening system was used to scan segments of the superficial femoral vein and assess them for compression. Vessel bifurcations were not scanned. When possible, more than one vessel segment per patient was scanned. When possible, calf veins were scanned.

The examinations, approved by the University of British Columbia Clinical Research Ethics Board, were carried out by two nurse practitioners after undergoing training for using the system. Compression data were gathered in compression-release cycles after having generated a 3D vessel model. A flow assessment was performed by measuring mean venous flow values, determined by color ultrasound, during rest and when the patient flexed their ankle.

All patients underwent an independent CUS examination in the Radiology Department to determine whether DVT was present, and this was used as the gold standard.

Classification

Multiple compound measures for DVT based on the TAR, slope and flow criteria were calculated and used in the classification and calculation of an optimal feature approach as described in "Classification for DVT" section. Using mean and maximum values per model for each scanned vessel segment, "global" DVT measures were generated for each segment.

An outlier removal approach was used to refine the data. Using the slope criteria, it was determined whether any data point is farther than a given threshold from the line fit to the data. If so, that point is marked "invalid" and the slope is recalculated. The TAR is calculated using only the remaining "valid" points.

The number of outlier points removed is used as a parameter (1, many), where the slope criteria is recalculated until all points are within the given threshold if many points are to be removed, or alternately only one point is removed, that with the largest error. In addition, two distance thresholds (small and large) were used.

An additional set of measures was calculated based on the slope criteria, except that the force values used in the calculation were not normalized. Otherwise, this criteria was calculated in the same manner as the slope described in "Compressibility criteria" section. The outlier removal approach was also applied to the data obtained using these measures.

In total, 17 measures were calculated and used for classification of the patient data. These are presented in Table 1, with the parameters used for their calculation indicated therein. Only vessel scans that had compressibility data (TAR and slope) and flow data (flow ratio) were considered for the compound measures to determine DVT; otherwise, they were not included in this analysis. In some cases, we were unable to acquire flow data because of a lack of flow data from the ultrasound machine, which is a common and known complication when imaging with color Doppler ultrasound.

Optimal features were calculated for all combinations of the different measures, using combinations of two, three and so forth up to 17 compound measures. The sensitivity and specificity of each of the optimal features were determined using a leave-one-out validation approach. Leave-one-out cross-validation is a valid statistical method where almost all data are used for training, and one final data point is used for evaluation. This procedure is repeated until all points are used for validation. In this manner, any optimal feature obtained from the combined measures that provided 100 % sensitivity and specificity was noted. The J value for each of these noted combinations was calculated.

Results

A total of 19 patients were scanned, aged 47–78 (mean 66.7), for a total of 26 limbs. Of these, four patients were positive for DVT, corresponding to seven vessels positive for DVT that were scanned using our system.

The compressibility measures for DVT that have been described were calculated online by the DVT screening system, as was the flow ratio criteria. The compound measures described in "Data acquisition" section were calculated offline, either from the online compressibility results or by recalculating the criteria using the stored data.

The J values for the individual DVT measures are presented in Table 2, as well as the sensitivity and specificity of each. These results are used as a reference to which the optimal features could be later compared. The highest J value corresponds to the flow ratio criteria. However, the J value is still very close to one, indicating that this measure may not be very good at classifying patients with DVT, and although sensitivity is 100 %, the specificity of 70 % is still low.

The combinations of individual measures that generated an optimal feature with maximum sensitivity and specificity were then identified. An exhaustive search was carried out

Table 2 DVT detection of individual measures

Measure label	J value	Sensitivity (%)	Specificity (%)
TAR-1	0.9232	66.7	66.7
TAR-2	0.9372	50.0	57.1
Slope-1	0.9709	50.0	66.7
Slope-2	1.0324	66.7	76.2
TAR-3	0.9556	60.0	64.0
TAR-4	0.9560	60.0	64.0
Slope-3	1.0083	60.0	64.0
Slope-4	1.0027	60.0	76.2
Slope-5	0.9773	40.0	66.7
Slope-6	1.0640	60.0	76.2
Slope-7	0.9915	60.0	69.6
Slope-8	1.0228	40.0	76.2
TAR-5	0.9623	66.7	67.9
TAR-6	0.9592	50.0	65.5
Slope-9	1.0209	50.0	70.4
Slope-10	1.0612	50.0	67.9
Flow-1	1.0973	100.0	70.0

Performance of the individual measures for DVT detection in terms of sensitivity and specificity, for the data set. Also shown is the J value, indicating how much better than chance (>1) the given criteria is

Table 3 Optimal features for DVT detection

[d]	J	[e]	[f]
OF-1	9.2541	TAR-2, Slope-1, Slope-2, Slope-4, Slope-8, TAR-5, TAR-6, Slope-9, Slope-10, Flow-1	10
OF-2	6.4280	TAR-2, Slope-2, Slope-3, Slope-4, Slope-8, TAR-5, TAR-6, Slope-9, Slope-10, Flow-1	10
OF-3	9.3620	TAR-2, Slope-1, Slope-2, Slope-3, Slope-4, Slope-8, TAR-5, TAR-6, Slope-9, Slope-10, Flow-1	11
OF-4	44.2120	TAR-1, TAR-2, Slope-1, Slope-2, TAR-4, Slope-3, Slope-4, Slope-6, Slope-8, TAR-6, Slope-9, Slope-10, Flow-1	13
OF-5	239.3107	TAR-1, TAR-4, Slope-3, Slope-4, Slope-5, Slope-6, Slope-7, Slope-8, TAR-5, TAR-6, Slope-9, Slope-10, Flow-1	13
OF-6	11.6423	TAR-1, Slope-1, Slope-2, TAR-3, TAR-4, Slope-3, Slope-4, Slope-5, Slope-8, TAR-5, TAR-6, Slope-9, Slope-10, Flow-1	14
OF-7	9.5800	TAR-1, Slope-1, Slope-2, TAR-3, TAR-4, Slope-3, Slope-4, Slope-5, Slope-6, Slope-7, TAR-5, TAR-6, Slope-9, Slope-10, Flow-1	15

[d] Optimal feature label
[e] Compound measures used for optimal feature
[f] Number of compound measures used for optimal feature calculation. J values $\gg 1$ indicate that the optimal features calculated from the compound DVT measures are useful for detecting DVT. All optimal features in this table had 100 % sensitivity and 100 % specificity for DVT

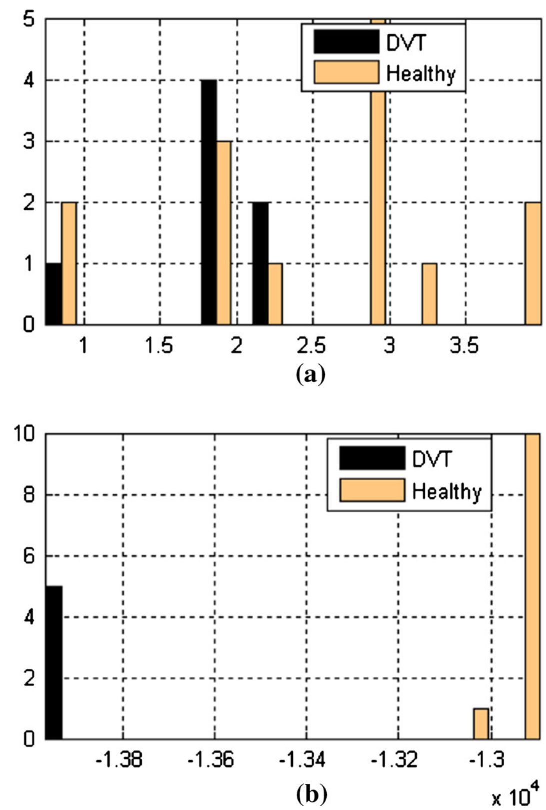

Fig. 4 Comparison of the **a** flow ratio criteria (Flow-1) and **b** one of the optimal features (OF-5) for detecting DVT. It is clear from **a** that flow ratio values (x-axis) for healthy and diseased individuals overlap, from which either false positives or negatives can arise. However, the optimal feature values (x-axis) for healthy and diseased cases are noticeably different. The y-axis in both cases denotes scan counts

for combinations of all 17 features indicated in Table 2. Only those combinations that yielded 100 % sensitivity and 100 % specificity were selected for further analysis. Seven such cases were found, and these are presented in Table 3. The individual DVT features found for each of the combinations are clearly indicated in the third column. The resulting J values for the optimal features were calculated using Eqs. (3)–(5), but the values for $\mathbf{X}_1$ and $\mathbf{X}_2$ are calculated using the samples from the specific compound measures indicated in the table, for each of the optimal features.

Figure 4 compares the single measure with highest J value and sensitivity, Flow-1, with the optimal feature with the highest J value, OF-5.

Discussion

A new approach has been presented for detecting DVT using an optimal feature calculated from simple, ultrasound-based DVT criteria. This approach results in a drastic increase in the measure of usefulness used to evaluate the measures, and perfect DVT detection was obtained for the test set of clinically relevant data. In addition, this new detection procedure can be immediately implemented since it is based on an existing system.

The system presented here is novel in at least two ways: (1) In addition to acquiring data used to calculate the compressibility measures, Doppler flow data are acquired at the same, centered on the vessel that is detected automatically, and (2) we propose a compound measure that combines compression and flow measurements to generate a single DVT criteria.

The current approach to screening for DVT relies on a single compound measure, such as the mean or maximum value of TAR or slope values of a scanned vessel or the flow ratio, in order to determine whether DVT is present. While satisfactory results in terms of detection (sensitivity) can be obtained from a single measure, the proper exclusion of negatives has remained difficult. This is illustrated by the results from the flow ratio (Flow-1) in Table 2. In a clinical setting, correctly identifying these negatives is important, in order to avoid unnecessary or over-treatment of DVT, which can in turn have serious consequences such as hemorrhaging. In addition, while some of the individual measures in Table 2 have varying values of sensitivity and specificity, the usefulness of these measures as indicated by the J value is very similar, and at times no better than chance (measure is $\sim$1).

By combining the multiple measures using a classification framework, we were not only able to obtain sensitivity and specificity of 100 %, but we were able to increase the J value up to over two orders of magnitude. This indicates that by representing the same data, that is, the raw data used to calculate the TAR and Slope values, and by recombining it using the classification scheme, more and better information has been obtained.

It is interesting to note that all the optimal features with 100 % sensitivity and specificity were obtained by including the Flow-1 measure. This indicates that the flow ratio provides a great deal of information on the possibility of DVT.

In addition, we believe that it is significant that the TAR-6 measure—one of the measures where the outlier removal approach has the least effect, since only one point is marked invalid and a large distance threshold is used—is also present in all optimal features. Similarly, the other measures where a large distance threshold is used for outlier removal (TAR-5, Slope-9, Slope-10) are present in all but one optimal feature. This may indicate that the use of a linear approximation for the compression profile of applied force vs. transverse area may not be adequate. All optimal features also include at least one modified slope measure, indicating that the applied force and its range may be important for identifying DVT, and the normalization of the force data for the slope calculation may be masking useful information.

We consider that the results of this novel combination of previously published measures help us understand what kind of measures and imaging are needed in order to identify DVT with high accuracy. Furthermore, the evaluation has been performed on clinical data in a clinical setting, lending further weight to the results. The combination of these measures leads to a new imaging modality in which a vessel model, tagged with a combined measure, can be displayed to the user as an accurate and objective measure of DVT.

Conclusions

A novel approach for detecting DVT using an optimal measure calculated from ultrasound data has been presented. Using multiple compressibility and flow measures calculated from ultrasound and sensor data, a single optimal feature was calculated. This optimal feature was shown to have 100 % sensitivity and specificity when tested on patient data from the Orthopaedics ward at the University of British Columbia Hospital. In addition, there was an increase in the measure of usefulness used to evaluate the measures of more than two orders of magnitude when comparing the optimal feature to the best single feature.

To our knowledge, there is currently no clinical measure that provides 100 % sensitivity and 100 % specificity for DVT detection. It is true that the measures used as data sources (compressibility and flow) have been well studied, but individually the results obtained were not better than existing clinical practices (e.g., compression ultrasound). In addition, the previously studied measures have been examined individually, and not as a single compound measure. We believe that demonstrating an objective measure with 100 % sensitivity and 100 % specificity is highly significant, and more so considering that the system does not require training.

The power of our results is not yet sufficient to be conclusive, and evaluation on larger datasets would be appropriate, but this is a new measure that is very promising, and has been evaluated in 19 patients with a complex system ready for clinical use.

Acknowledgments The authors would like to thank Leah Christoff and Jean Hong for their invaluable collaboration with data collection. This research was funded in part by MITACS, a Network of Centres of Excellence, PRECARN and NSERC.

Conflict of interest J.A. McEwen is President of Western Clinical Engineering, Ltd., and B.A. Masri and S. Nicolaou are affiliated with both the University of British Columbia and Vancouver Coastal Health. S. Salcudean and J. Guerrero declare no conflict of interest.

Ethical standard All procedures performed in studies involving human participants were in accordance with the ethical standards of the University of British Columbia, as approved by the Ethics Review Board of the University, and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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