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Research Paper

Validation of a computerised technique for automatically tracking and measuring the inferior vena cava in ultrasound imagery

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Accurate resuscitation of the critically-ill patient using intravenous fluids and blood products is a challenging, time sensitive task. Ultrasound of the inferior vena cava (IVC) is a non-invasive technique currently used to guide fluid administration, though multiple factors such as variable image quality, time, and operator skill challenge mainstream acceptance. This study represents a first attempt to develop and validate an algorithm capable of automatically tracking and measuring the IVC, compared to human operators across a diverse range of image quality. Minimal tracking failures and high levels of agreement between manual and algorithm measurements were demonstrated on good quality videos. Addressing problems such as gaps in the vessel wall and intra-lumen speckle should result in improved performance in average and poor quality videos. Semi-automated measurement of the IVC for the purposes of non-invasive estimation of circulating blood volume poses challenges, but it is feasible.

1. Introduction

Accurate resuscitation of the critically-ill patient using intravenous fluids and blood products is a challenging, time sensitive task. Insufficient, excessive or delayed administration increases patient morbidity and mortality (Durairaj & Schmidt, 2008; Marik & Cavallazzi, 2013; Rivers et al., 2001). Traditional methods used to guide volume resuscitation, such as the central venous pressure (CVP), are invasive and are recognised as poor predictors of fluid-responsiveness—defined as fluid administration with a resultant increase in stroke volume (Marik & Cavallazzi, 2013). In recent years, clinicians have increasingly been using portable ultrasound to image the inferior vena cava (IVC) in critically-ill, ventilated patients as a means of determining fluid responsiveness and guiding fluid therapy (Anderson, Jenq, Fields, Panebianco, & Dean, 2013; Machare-Delgado, Decaro, & Marik, 2011). For illustrative purposes, a typical scenario would involve a physician generating and interpreting an ultrasound video of the IVC, estimating both the size and respiratory variation in real-time without ever leaving the bedside.

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The main evidence supporting ultrasound of the IVC as a tool to guide volume resuscitation in the mechanically ventilated patient comes from two independent studies conducted in 2004. Barbier et al. (2004), Feissel, Michard, Faller, and Teboul (2004) demonstrated that respiratory variability—the relative change in size of the IVC over a respiratory cycle—of approximately 15% identified fluid responders with high sensitivity and specificity.

Ultrasound of the IVC does have its limitations. Unfortunately, both image generation and interpretation using ultrasound are skill dependent creating potential for significant inter-operator variability (Akkaya, Yesilaras, Aksay, Sever, & Atilla, 2013). IVC image quality is affected by a number of factors including body habitus, bowel gas, ultrasound artefact and relative depth of the IVC in the body. Other limitations include the time necessary to conduct serial measurements during resuscitation as well as estimation errors associated with multiple measurements over time. These combine to decrease the practical utility of ultrasound as a non-invasive monitoring solution.

Significant work regarding segmentation and tracking of arterial vascular structures in ultrasound imagery has been published though few studies focus on the venous network (Acton &Ray, 2006; Acton & Ray, 2009; Egger, Krasinski, Rutt, Fenster, & Parraga, 2008; Maiora, Ayerdi, & Graña, 2014). The fundamental problem associated with automated segmentation of the IVC in ultrasound videos is that the anatomical structures are highly deformable and that the boundaries between them are not always distinct. Traditional tracking and segmentation techniques developed for rigid objects in scenes with a clear foreground and background are not directly applicable (Acton & Ray, 2006). Guerrero, Salcudean, McEwen, Masri, and Nicolaou (2007) demonstrated promising methodology and results with their work using a modified star-Kalman filter to improve screening for deep vein thrombosis. More directly related to volume status, Qian et al. (2013) explored the problem of segmenting the venous vasculature using active contour and speckle tracking techniques to measure the size and respiratory variation of the internal jugular vein. These articles highlight some key techniques and approaches to tracking and segmenting superficial vascular structures with inherently good image quality and with less variability. To the best of our knowledge, this paper details the first published attempt towards developing an algorithm designed to track and measure both the diameter and respiratory variation of the IVC and overcome several of the previously described limitations.

2. Methods

2.1. *Proposed algorithm*

The algorithm (CAVUS) used in this paper is semi-automated and applies a modified watershed approach. Watershed segmentation schemes have been used in similar contexts in the past with variable success, with one such example being the work on segmenting the carotid artery by Abdel-Dayem, El-Sakka, and Fenster (2005). The modified watershed approach highlighted in this paper consists of 5 steps and was selected for its computational efficiency as a reasonable first attempt.

Step1: Pre-processing

Ultrasound image quality is usually affected by different types of noise such as speckle, thermal and electronic noise. A 7 x 7 blur filter is used to reduce the impact of noise on the algorithm's performance.

Step 2: Initialisation

The candidate IVC is identified and a marker of the candidate IVC's centroid ($m_{t,i}$) calculated at time t and image location i. At $t = 0$, the operator manually selects the centre point and defines maximum radius around the expected location of IVC.

Step 3: IVC detection

The IVC is extracted from the background using a watershed-based algorithm that utilises the detected markers $m_{t,i}$ as seed points with markers growing to fill the IVC. The list of markers are represented by M_t where $m_{t,i} \in M_t$. The algorithm is implemented recursively at each step n at time t, a new list $M_t[n]$ is obtained from previous $M_t[n-1]$ as follows:

1. Find all connected components; denoted as C[n].
2. Perform a morphological dilation.
3. Find the intersection (IntrSct) between all connected components where

$$\text{IntrSct} = \left\{ res_{t,i} \middle|\; res_{t,i} = c_{t,i} \cap M_t[n-1],\;\; c_{t,i} \in C_t[n] \right\} \tag{1}$$

4 Then

$$M_t[n] = \begin{cases} AddNew\,(c_{t,i}), & \|res_{t,i}\| = \varnothing \quad \forall\; res_{t,i} \in IntrSct \\ Add\,(c_{t,i}), & \|res_{t,i}\| = 1 \quad \forall\; res_{t,i} \in IntrSct \\ BuildDam(c_{t,i}, c_{t,j}), & \|res_{t,i}\| \geq 2 \quad \forall\; res_{t,i} \in IntrSct \end{cases} \tag{2}$$

where $\|res_{t,i}\|$ is the number of intersections; $AddNew(c_{t,i})$ denotes incorporating new objects; $Add(c_{t,i})$ denotes copying from $M_t[n-1]$ to $M_t[n]$ directly; $BuildDam(c_{t,i}, c_{t,j})$ represents constructing a dam between the intersected objects to prevent overflow.

5 Repeat until reaching maximum gray level of the filtered image.

Step 4: Result filtering

The detected IVC from step 3 is further filtered according to the temporal area of IVC in consecutive frames using the equation

$$IVC\_list_t = \begin{cases} Add\,(m_{t,i}), & T1 < Area(m_{t,i}/(m_{t-1,i})) < T2 \\ ignore\,(m_{t,i}) & \text{otherwise} \end{cases} \tag{3}$$

In order to filter and reject very small IVC and very large IVC, the ratio between area of $m_{t,i} \in M_t$ and area of $m_{t-1,i} \in M_{t-1}$ must be within T1 and T2 where T1 < T2.