Towards a quantitative *in vivo* evaluation of venous blood echogenicity: Image processing versus subjective assessment

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Abstract. Purpose: Spontaneous blood echogenicity in vein ultrasound images may be a marker for an increased erythrocyte aggregability, but a reliable quantitative evaluation method is a prerequisite for its use in clinical studies. We compared a simple scoring system of blood echogenicity intensity and pattern, with automatic image analysis.

Material and methods: 157 femoral and popliteal vein digitized ultrasound sequences were reviewed by two independent observers who chose an image, delimited an area of interest (ROI), and graded blood echogenicity intensity and pattern, using a four class score. Each observer reviewed the images selected by the other, without and with ROI. The computer calculated first and second order parameters describing echo intensity and spatial organization.

Results: Inter-observer reproducibility of subjective assessment was poor (Kappa < 0.5), whereas the automatically calculated ROI average gray level intensity relatively to the whole image ($\tau_1$) effectively separated all grades of intensity. No parameter effectively separated patterns.

Conclusion: $\tau_1$ is a simple parameter for the *in vivo* evaluation of blood echogenicity intensity. It should be evaluated in standardized conditions for clinical hemorheology studies in correlation with *in vitro* erythrocyte aggregation measurements.

Keywords: Ultrasound, vein, blood, echogenicity, image analysis, computer

1. Introduction

Spontaneous echogenicity of the flowing blood is very commonly seen on B-mode ultrasound images of peripheral veins (often referred to as “spontaneous blood flow echogenicity”) [1–3] as well as in the atrium and left atrium appendage during echocardiography examination (often referred to as “spontaneous echocardiographic contrast”) [4–7].

Most authors acknowledge that spontaneous blood echogenicity is mostly related to blood stasis [8–10], facilitating red cell aggregation [11], modulated by plasma proteins [12–21]. Spontaneous
echocardiographic contrast have been associated with a hypercoagulable state [22] and an increased rate of thromboembolic events [23–28].

In contrast with the large number of reports concerning spontaneous echocardiographic contrast and the thrombo-embolic risk it implies, very few studies have described and analyzed in vivo spontaneous blood echogenicity in peripheral vessels, although this is a very common finding. In vitro studies demonstrated greater blood echogenicity in patients with arterial claudication [29], or with suspected venous thrombosis [15]. In vivo, spontaneous blood echogenicity is commonly seen in the lower limb veins of healthy subjects when blood stasis is induced by the sitting position [9]. During uncomplicated pregnancy, increased lower limb vein diameter, together with a decrease in hematocrit and an increase in fibrinogen concentration, result in spontaneous blood echogenicity in the femoral veins, which has to be considered as a physiological phenomenon [3]. In the aorta, spontaneous blood echogenicity was found especially in older, male patients with a large aorta and complex atherosclerosis, and was associated with a high prevalence of embolic events [30].

In our clinical practice, spontaneous blood echogenicity is a very common phenomenon that we have to interpret in reference to the position and clinical status of the subject. In lower limb veins, blood stasis may be induced by any mechanical obstacle along the venous path (a venous thrombus as well as extrinsic compression by an aneurysm, hematoma, popliteal cyst, etc.) [31] or increased abdominal pressure. Therefore, spontaneous blood echogenicity may be a clue to the positive and differential diagnosis of venous thrombosis. On the other hand, when not explicable by stasis, spontaneous blood echogenicity may suggest some underlying rheological or hematological disorder, with increased thromboembolic risk. As blood stasis itself constitutes a risk factor for thrombosis, spontaneous blood echogenicity could be proposed as a marker of thromboembolic risk. Nevertheless, large prospective studies would be necessary to assess the exact significance of this phenomenon, and to validate its clinical use. A major drawback for the setup of such studies is that the level of blood echogenicity depends largely on machine settings, while its evaluation is highly operator dependent. Therefore, observation conditions have to be standardized, and an evaluation method has to be precisely defined and its reproducibility assessed before any prospective study can be planned and performed.

The ideal method for grading blood echogenicity should be both machine and operator independent. As there are many different ultrasound systems on the market, and as they are used in many different ways to obtain the same diagnostic information, standardization of image acquisition should be reduced to simple and universal recommendations. On the other hand, the scoring system should be detailed enough to allow the detection of minor changes in blood echogenicity during longitudinal or pharmacological studies.

The aim of our study was therefore to evaluate the reproducibility of a simple scoring system of blood echogenicity, and its comparison with automatic image analysis by first and second order parameters describing echo intensity and spatial organization.

2. Material and methods

During lower limb vein ultrasound examination of patients referred to the Vascular Laboratories of the two participating University Hospitals for suspicion of deep venous thrombosis, video sequences were routinely stored on a computer for subsequent review and archiving. An anonymous thesaurus of femoral and popliteal vein video sequences was constituted from these archives.

Lower limb vein examinations were conducted by several medical doctors following the same protocol. The patient was lying supine on a strictly horizontal bed, at rest and breathing normally. B-mode
ultrasound sequences were acquired with Acuson 128 XP or Aspen systems (Acuson, Mountain View, CA) with a 7.5 linear array probe. The machine settings were initially identical (peripheral vein preset), but could be freely altered when necessary, depending on the vein depth and overall echogenicity.

The Y/C video signal was digitized via the built-in video frame grabber and sequences were stored as movies on a Macintosh 8500/180 PowerPC computer. Image processing and analysis was then performed independently, with IÔ 3.1 software (IÔDP, Paris) and a dedicated analysis and calculation software module developed in the laboratory.

Two independent observers read each sequence, selected one or several representative images (provided that images from the same patient corresponded to different veins or different parts of a vein, so that there was no duplicate), drew the area or “region of interest” (ROI) perimeter around the representative part of the B-mode image 1 (i.e. the part of the vein lumen showing spontaneous blood echogenicity, if any, or the greater artifact free part of the vein lumen when no blood echogenicity could be seen), and subjectively evaluated the intensity and spatial organization of blood echogenicity (Fig. 1). Each observer was blinded from the patient’s identity and clinical status, as well as from the other observer’s assessment and from calculation results of the software module. Both observers were medical doctors, with more than 2 years’ (B) or 20 years’ (A) experience of vascular sonography. They reviewed together twenty studies before starting the project.

The analysis was performed in three steps: (1) Observer A read each movie, selected freely one or several representative images, drew freely the ROI, and subjectively evaluated blood echogenicity. Observer B did the same, independently. Images and ROIs selected by each observer were stored. (2) Ob-

Fig. 1. Example of femoral vein ultrasound image with the ROI encircling the area in which the observer detected spontaneous blood echogenicity. Anonymous sequence and image identification appears on the top of the screen, while software tools appear on the right side.
server A read each image selected by observer B (without observer B’s ROI), drew freely his own ROI, and subjectively evaluated blood echogenicity. Observer B did the same with images selected by observer A. (3) Observer A subjectively evaluated blood echogenicity of each image selected with ROI drawn by observer B. Observer B did the same with images selected with ROIs drawn by observer A. At step 1 and 2, the computer software module calculated two sets of parameters characterizing blood echogenicity in the ROI.

2.1. Subjective evaluation and grading by two independent observers

Subjective grading of the intensity of spontaneous blood echogenicity on B-mode ultrasound images of peripheral veins was performed according to the following scale [3]: grade 0, anechoic (no echo visible in the lumen); grade 1, barely visible echoes in the lumen; grade 2, clearly visible echoes whose intensity remained lower than that of surrounding tissues; grade 3, blood echogenicity equal to or greater than the echogenicity of surrounding tissues.

The pattern of blood echogenicity was subjectively assessed in order to differentiate the swirling echogenicity of flowing blood, commonly described as “smoke”, from echogenic clumps or filaments. Classification was as follows: 1, homogeneous echogenicity; 2, echogenic clumps or filaments; 3, mixed echogenicity pattern.

2.2. Objective image processing and analysis by computer software

Image analysis was performed in the ROI drawn by the observer by a dedicated software module including user interface and calculation algorithms, written in C programming language with CodeWarrior V3.0 integrated development environment (Metrowerks, Austin, TX). This software automatically calculated two sets of first and second order parameters [32,33] describing the absolute and relative gray level intensity of echoes in the ROI, as well as the spatial organization of spontaneous blood echogenicity, if any.

With \( N_I \) the total number of pixels in the whole image \( I \); \( N_{ROI} \) the number of pixels in the ROI; \( \overline{ROI} = I - ROI \); \( N_{ROI} \) the number of pixels in \( ROI \); and \( I_{(i,j)} \) the gray level intensity of a given pixel whose coordinates are \( i \) and \( j \); a first set of parameters was calculated to describe the gray level intensity or “echogenicity”:

Average gray level intensity of the ROI

\[
m_{ROI} = \frac{1}{N_{ROI}} \sum_{k=1}^{N_{ROI}} I_{(i,j)}. \tag{1}
\]

Average gray level intensity outside the ROI

\[
m_{\overline{ROI}} = \frac{1}{N_{\overline{ROI}}} \sum_{k=1}^{N_{\overline{ROI}}} I_{(i,j)}. \tag{2}
\]

Average gray level intensity of the whole image

\[
m_I = \frac{1}{N_I} \sum_{k=1}^{N_I} I_{(i,j)}. \tag{3}
\]
Average gray level intensity of the ROI relative to the whole image
\[ \tau_1 = \frac{m_{ROI}}{m_I}. \] (4)

Average gray level intensity of the ROI relatively to the image outside the ROI
\[ \tau_2 = \frac{m_{ROI}}{m_{ROI}}. \] (5)

Local variance of gray level intensity in the ROI (a smooth image has a small variance)
\[ \sigma^2 = \frac{1}{N_{ROI}} \sum_{k=1}^{N_{ROI}} (I(i,j) - m_{ROI})^2. \] (6)

Skewness of ROI, measuring the asymmetry of the frequency distribution histogram of pixels gray levels
\[ ske = \frac{1}{N_{ROI}} \sum_{k=1}^{N_{ROI}} \left( \frac{I(i,j) - m}{\sigma} \right)^3. \] (7)

Kurtosis of ROI, indicating the flatness of the histogram
\[ kur = \frac{1}{N_{ROI}} \sum_{k=1}^{N_{ROI}} \left( \frac{I(i,j) - m}{\sigma} \right)^4. \] (8)

Regional Entropy of ROI, describing the image detail and clutter
\[ Ent_R = -\frac{1}{N_{ROI}} \sum_{k=1}^{N} I(i,j) \ln I(i,j)1_{I(i,j)} \] (9)

with \((i,j) \in R\) and \(1_{I(i,j)} = 1\) if \(I(i,j) \neq 0\) and \(1_{I(i,j)} = 0\) if \(I(i,j) = 0\).

Kolmogorov–Smirnov test of ROI, measuring image homogeneity \(KS(H, H_0)\) (see Appendix A).

The co-occurrence matrix [34,35] (see Appendix B) was used for the calculation of a set of second order parameters (see Appendix C), relative to the spatial organization and texture of the ROI [32,36], with \(\theta = 0^\circ\) and \(90^\circ\), and \(d = 1\), because these values are commonly used for the analysis of ultrasound images [35]. This set of parameters included contrast \((CON_{\theta,d})\) as a measure of the variation in intensity between pixels, energy \((ENE_{\theta,d})\) as a measure of global image homogeneity, local homogeneity \((HOGL_{\theta,d})\), directional entropy \((ENTD_{\theta,d})\) as a measure of image disorder, correlation \((COR_{\theta,d})\) as a measure of correlation between two pixels, and \(KAP\) \((KAP_{\theta,d})\), as a measure of periodicity in the image [35]. The software calculated also \(CON, ENE, HOGL, ENTD, COR\), and \(KAP\) as the mean values of these parameters with \(\theta = 0^\circ, 45^\circ, 90^\circ, \) and \(135^\circ\), and \(d = 1\) (for example: \(CON = (CON_{0,1} + CON_{45,1} + CON_{90,1} + CON_{135,1})/4\)).
2.3. Statistical analysis

The statistical analysis was performed with SAS V6.06 software (SAS Institute Inc, 1987 Cary, NC). Agreement between observers was assessed by the Kappa test while disagreement between observers was assessed by McNemar’s test, for each intensity grade and pattern of blood echogenicity, and each class of image quality, separately and after pooling. For each subjective parameter and each observer, analysis of variance was performed to compare the calculated parameters for each of the observer’s grades. When analysis of variance showed significant differences between groups, the Newman–Keuls post-test was used to identify the differences between the grades. Inter-observer differences in calculated parameters at step 1 and 2 were evaluated by the Student’s t test for paired data. Correlation between parameters calculated at step 1 and step 2 for observer A and observer B was evaluated by Pearson’s parametric and Spearman’s non-parametric correlation coefficients.

Multivariate analysis using the logistic model was performed to explain each subjective parameter by the most informative calculated parameters. For each set of calculated parameters, an unconditional logistic regression was performed to select the most informative variables, that were introduced into a global multivariate logistic model to control for all the confounding calculated parameters, as described by Hosmer and Lemeshow [37]. For model building, we have applied forward stepwise introduction of variables (p-entry 0.05). Results were considered as significant when \( p < 0.05 \).

3. Results

From 157 examination sequences of 75 patients, observer A selected and analyzed 193 images, whereas observer B selected 136 images (step 1).

At step 2, observer A read the 136 images selected by observer B and drew and analyzed 142 ROIs, while observer B read the 193 images selected by observer A and drew and analyzed 196 ROIs (in some instances, the observer read the same image twice and drew different ROIs). At step 3, observer A analyzed 143 images selected with ROIs drawn by observer B (one image was read twice), while observer B analyzed 173 images selected with ROIs drawn by observer A (20 images were not read). Each ROI included at least 1000 pixels.

3.1. Inter-observer reproducibility of subjective assessment

Inter-observer reproducibility for intensity of spontaneous blood echogenicity evaluation was poor (Kappa < 0.5) except when grade 1, 2, and 3 were pooled and compared to grade 0 at step 1 (Kappa = 0.57, \( p < 0.001 \)), at step 2 (Kappa = 0.57, \( p < 0.001 \)), and at step 3 (Kappa = 0.7, \( p < 0.001 \)). For the pattern of blood echogenicity, inter-observer reproducibility was poor at each step and for any pooling method.

3.2. Blood echogenicity intensity and calculated parameters

For observer A, \( \tau_1 \) (Fig. 2), \( \tau_2 \), \( m_{ROI} \), \( \sigma^2 \), \( KS(H, H_0) \), \( HOGL_{0,1} \), \( ENT_R \), and \( CORL_{0,1} \) reliably separated all grades of blood echogenicity intensity. Some parameters (ske, kur, \( ENE_{0,1} \), \( HOM_{90,1} \), \( CORL_{90,1} \), \( COR \)) separated grade 0 from grade 1, 2, or 3 (but not grades 1, 2, and 3 from each other). Other parameters (\( KAP_{0,1} \), \( HOGL_{90,1} \), \( ENTD_{90,1} \), \( KAP_{90,1} \), \( CON \), \( ENE \), \( HOGL \), \( ENTD \), \( COR \), and \( KAP \)) separated grade 0
from grade 1 and from grades 2 or 3 but not grades 2 and 3 from each other. One parameter \((CON_{90,1})\) separated grades 0 or 1 from grades 2 or 3 but neither grade 0 from grade 1 nor grade 2 from grade 3.

For observer B, \(KAP_{0,1}\) separated grade 0 or 1 from grade 2 or 3 but not grade 0 and 1 from each other. \(CON\) and \(HOGL\) separated only grade 0 from grade 3. \(COR\) separated only grade 0 from grade 2. \(CON_{90,1}\) and \(COR_{90,1}\) could not separate any grade. All other parameters separated grade 0 from grades 1, 2, or 3, but not grades 1, 2, and 3 from each other.

The Pearson parametric correlation coefficient for \(\tau_1\) was 0.8 \((p < 0.0001)\) at step 1 and 0.8 \((p < 0.0001)\) at step 2. The Spearman correlation coefficient for \(\tau_1\) was 0.9 \((p < 0.0001)\) at step 1, and 0.84 \((p < 0.0001)\) at step 2.

Multivariate analysis of observer A’s results identified \(\tau_1\) \((p = 0.0023)\) and \(\sigma^2\) \((p = 0)\) as the only independent parameters separating grade 0 or 1 from grade 2 or 3, with a 89.1% concordance rate. There was no significant difference in \(\tau_1\) \((p = 0.65\) and 0.43\) and in \(\sigma^2\) \((p = 0.97\) and 0.88\) between ROIs selected by observer A and observer B, respectively on the same sequences (step 1) and on the same images (step 2).

### 3.3. Blood echogenicity pattern and calculated parameters

Pattern 2 was recognized in 9 cases by observer A, and in 16 cases by observer B. For observer A, \(ENTR\) separated pattern 2 from pattern 3, while \(CON_{90,1}\), \(CON\), and \(HOML\) separated pattern 2 from patterns 1 or 3, but not pattern 1 from pattern 3. For observer B, \(\tau_1\) and \(\tau_2\) separated all patterns, while \(m_{ROI}\), \(HOML_{0,1}\), \(CON_{90,0}\), \(HOML_{90,0}\), \(CON\) and \(ENE\) separated pattern 2 from pattern 1 or 3, but not pattern 1 from pattern 3. Pattern 2 and 3 were separated by \(\sigma^2\), \(ENTD_{0,1}\) and \(KAP\), whereas pattern 1 was separated from pattern 3 by \(COR_{0,1}\) and from pattern 2 by \(COR\).

### 4. Discussion

On the basis of \textit{in vitro} [38], and \textit{in vivo} [39] studies, protein mediated erythrocyte aggregation appears to be the main mechanism of spontaneous blood echogenicity. \textit{In vitro} studies showed that hematocrit...
affected the rate of cell aggregation while fibrinogen controlled aggregate size and acoustic concentration [19]. Clinical studies confirmed the role of hematocrit, plasma viscosity, fibrinogen and plasma paraproteins [20,21]. The intensity of blood echogenicity results, on one hand, from technical factors (especially ultrasound frequency and signal processing), and, on the other hand, from several biological factors (hematocrit, flow velocity, turbulence, pulsatility, and fibrinogen concentration) that determine erythrocyte aggregation [40]. The relationship between hematocrit and ultrasound backscattering by blood is complex: backscattering increases with hematocrit at low hematocrit values, then decreases [41,43]. Shear rate and red cell aggregation alter this relationship in a complex way [44]. As the backscattered ultrasonic intensity depends on the size of erythrocyte aggregates [41,45], B-mode ultrasound has been used for in vitro evaluation of red cell [46] and platelet aggregation [47], and backscatter intensity is thought to provide an objective, quantitative method for the evaluation of blood echogenicity [48,49].

Semi-quantitative methods have been used for the grading of blood echogenicity and echocardiographic contrast on B-mode ultrasound images [21,50,51]. Only one study assessed the inter-observer variability of subjective spontaneous echo-contrast detection, and reported low variability [52], but we found no paper in the literature assessing the reproducibility and reliability of a scoring system. Quantitative video-densitometry was used by Fatkin et al. for the evaluation of spontaneous contrast on echocardiographic images [38], and for the evaluation of red cell aggregation in forearm subcutaneous veins by Kitamura et al. [39], but we found no data regarding the inter and intra-observer reproducibility of such techniques. Automatic analysis of B-mode ultrasound images by a set of first and second-order parameters have been used and validated for the characterization of carotid plaques [53], but has not been used so far for the evaluation of blood echogenicity.

In order to mimic the actual conditions of routine ultrasound vein examination, we designed a protocol allowing two independent observers to read and interpret the same ultrasound sequences, select the representative images, and delimit the part of the lumen showing spontaneous blood echogenicity, as if they were performing separately the examination of the same patient. The only limitation was that these sequences came from the same ultrasound device and were acquired with the same machine settings. Thus, our study could focus on subjective image interpretation and automatic image analysis, independently of technical parameters.

This study demonstrated that inter-observer reproducibility of the subjective assessment of blood echogenicity intensity and pattern is poor, except when observers are simply asked to answer by yes or no as for the presence of spontaneous blood echogenicity. Recent studies [54,55], yielded moderate to good agreement and demonstrated that reproducible grading of carotid plaque morphology was not consistently achievable, even by experienced observers, although inter-observer variability could be reduced by using binary classification [55]. In various fields, clinical studies demonstrated the relative inaccuracy of gray level perception [56]. No prospective clinical study is therefore possible on the sole basis of subjective grading, and a quantitative or semi-quantitative objective method is mandatory.

From the large sample of calculated parameters we tested, $\tau_1$ (average gray level intensity of the ROI relatively to the whole image) and $\sigma^2$ (local variance of gray level intensity in the ROI) were the main independent parameters reliably describing the intensity of blood echogenicity in concordance with observer A, and without significant difference between observers when they drew freely and independently a region of interest on the same sequence or on the same image. Nevertheless, its interpretation will have to remain cautious, because the relationship between the size of red cell aggregates and the intensity of blood echogenicity is neither linear nor explicit [57].
Various parameters have been used for B-mode ultrasound image characterization of carotid plaque, but we found no data in the literature regarding their use for the quantification of blood echogenicity. Some authors used the median of the gray scale [58,59] as well as homogeneity, entropy, and contrast, for the evaluation of carotid plaques, and found that the median was a good predictor of hemispheric symptoms [60,61]. Other authors found the normalized mean gray level to be the most effective first-order parameter for the description of carotid plaque morphology [53]. Second order parameters were used with no definitive results by Tanzi et al. for the study of the neonatal heart [62].

As for blood echogenicity patterns, class 2 (echogenic clumps or filaments) was separated from class 1 (homogenous blood echogenicity) or class 3 (mixed pattern) for both observers by \( \text{CON}_{90} \), \( \text{CON} \) (mean contrast value), and \( \text{ENE} \) (energy). Indeed, the relatively small number of cases in class 2 do not allow to validate definitely these parameters for this application. Second order parameters could not help differentiating blood echogenicity patterns, probably because spontaneous blood echogenicity showed no typical texture.

Recent ultrasound systems offer a remarkably large dynamic range, so that blood echogenicity may become visible in most vessels when increasing gain. Conversely, reducing the dynamic range may result in the disappearance of blood echogenicity. Gain and TGC settings may also alter the level of echogenicity. Blickstein et al. demonstrated that manipulation of image parameters by computed sonographic technology obviates accurate echogenicity assessment [63], so that precise and standardized setting of the B-mode ultrasound machine is a prerequisite for image characterization and quantification [64], although normalization reduces the machine and gains dependence [65]. Therefore, standardization of machine settings and image acquisition procedure is essential before any computer assisted diagnostic method can be used for multicentric, prospective studies, especially when different duplex scanning systems and ultrasound probes are to be used. Such standardization may be achieved by zooming on the relevant area, using the maximum dynamic range, with linear postprocessing curve, and using a standard procedure for the setting of the overall gain and TGC [66]. Stored images may also be normalized by algebraic scaling with reference to normally anechogenic and hyperechogenic anatomical structures, as the carotid lumen and adventicia for the study of carotid plaques [66], or by dynamic range adjustment when no reliable reference structure can be found, as it is the case in most studies of veins, because blood echogenicity precludes the use of the vessel lumen as a zero reference level. In our study, the physicians in charge of collecting video sequences shared a common background and training, so that they used to set the sonographic system in the same way, especially as regards overall gain and TGC. Nevertheless, they remained free to alter these settings in order to obtain the best image whenever technical or anatomical problems were encountered, because we felt that more strict rules could not be imposed in the clinical practice for multicentric studies involving different observers, different machines, and different conditions. We reduced the effects of machine settings by calculating relative parameters, and it is therefore quite demonstrative that the most effective parameter for the evaluation of blood echogenicity intensity was \( \tau_1 \), the average gray level intensity of the region of interest relatively to the whole image.

On the other hand, the cooccurrence matrix parameters depend on the number of diffuse scatterers and on the speckle size, which, in turn, is depth dependent, especially with sector scanning ultrasound probes [35]. We minimized this problem by using only linear probes, with the same transmitting frequency, and on a limited area (ROI).

Another potentially confounding variable is blood velocity, since red cell aggregation depends on shear stresses. Spontaneous blood echogenicity may be expected to occur more frequently in large veins with low flow velocity. Patients were examined in the same, resting conditions, but individual differences may
blur the threshold between normal and abnormal situations. This problem did not preclude the demonstration of spontaneous echocardiographic contrast as a risk marker for thrombosis, since blood echogenicity in the atrium is, almost always, an abnormal finding. On the contrary, spontaneous blood echogenicity in peripheral veins may be a perfectly normal finding in a healthy subject when blood stasis is created by posture or downstream compression. Therefore, models describing the in vivo relationship between flow velocity, vessel diameter, and red cell aggregation should be used to standardize the ultrasound examination in future clinical studies.

5. Conclusion

The average gray level intensity of the region of interest relatively to the whole image ($\tau_1$) may be used as a simple and easily calculated parameter for the automatic, objective evaluation of the intensity of spontaneous blood echogenicity, to provide a non invasive marker of in vivo erythrocyte aggregability. This parameter has still to be validated by large prospective studies, before its clinical significance can be evaluated. At this stage, the technical conditions of image acquisition will have to be checked and, when possible, standardized, while physiological conditions will have to be, as far as possible, carefully controlled. As for the analysis of the echogenicity pattern, additional research, with the use of image filtering techniques, validated on a larger scale, would be necessary before this characteristic can be reliably assessed and used in clinical studies.

Acknowledgements

This work was supported by a French State grant from the Délégation Régionale à la Recherche et à la Technologie (1997–1998). We thank Souheil Mansour (IÖDP, Paris, France) for his help in software design and editing. We thank Frédérique Vivens, MD, Patricia Ponsi, MD, Bénédicte Fada, MD, and Catherine Charria, MD, for their help in data collection and interpretation. We thank Margaret Manson for her help in manuscript revision.

Appendix A: Kolmogorov–Smirnov test calculation

The histogram $H$ of $I$ is a vector of dimension $L_g$, defined as:

$$H = \{H(I,e), e = 0, 1, \ldots, L_g - 1\}, \quad (A.1)$$

where $H(I,e)$ is the number of pixels whose gray level is $e$, and $L_g$ is the maximum gray level intensity of $I$, so that a set of $L_g$ different (distinguished) histograms can be obtained. The distinguished (or minimal) histogram $H_0$ is a histogram where all gray levels (from 0 to $L_g$) are evenly represented:

$$H_0 = \left\{H(I,e) = \frac{Ir \times Ic}{Lg}, \ e = 0, 1, \ldots, L_g - 1\right\}, \quad (A.2)$$

where $Ir$ and $Ic$ are respectively the number of rows and columns in $I$. 
The Kolmogorov–Smirnov test of the minimal histogram is the distance between the image histogram and minimal histogram:

\[
KS(H, H_0) = \sum_{0}^{L_g-1} (H(I, e) - H_0(I, e)).
\] (A.3)

**Appendix B: Co-occurrence matrix**

The co-occurrence matrix is a 2D histogram that describes the occurrence of pairs of pixels separated by a distance \(d\) in direction \(\theta\). For 2 pixels located respectively at the coordinates \((i_1, j_1)\) and \((i_2, j_2)\) with gray levels respectively \(I(i_1, j_1) = x\) and \(I(i_2, j_2) = y\), the normalized co-occurrence matrix \(M_{\theta,d}(x, y)\) is:

\[
M_{\theta,d}(x, y) = \frac{\text{Card}\left\{ ((i_1, j_1), (i_2, j_2)) \in I \times I / i_2 - i_1 = d \ast \sin \theta, \ j_2 - j_1 = d \ast \cos \theta \mid I(i_1, j_1) = x, I(i_2, j_2) = y \right\}}{N},
\] (B.1)

where \(\text{Card}\) is the number of elements in the set and \(N\) is the total number of pairs of pixels.

**Appendix C: Second order parameters**

The parameters contrast \((CON_{\theta,d})\), energy \((ENE_{\theta,d})\), local homogeneity \((HOGL_{\theta,d})\), directional entropy \((ENTD_{\theta,d})\), correlation \((COR_{\theta,d})\), and \(KAP\) \((KAP_{\theta,d})\) are defined by the following expressions:

\[
CON_{\theta,d} = \sum_{x=0}^{L_g-1} \sum_{y=0}^{L_g-1} (x - y)^2 M_{\theta,d}(x, y),
\] (C.1)

\[
ENE_{\theta,d} = \sum_{x=0}^{L_g-1} \sum_{y=0}^{L_g-1} (M_{\theta,d}(x, y))^2,
\] (C.2)

\[
HOGL_{\theta,d} = \sum_{x=0}^{L_g-1} \sum_{y=0}^{L_g-1} \frac{1}{1 + (x - y)^2} M_{\theta,d}(x, y),
\] (C.3)

\[
ENTD_{\theta,d} = -\sum_{x=0}^{L_g-1} \sum_{y=0}^{L_g-1} M_{\theta,d}(x, y) \ln M_{\theta,d}(x, y) 1_{M_{\theta,d}(x, y)},
\] (C.4a)

where

\[
1_{M_{\theta,d}(x, y)} = 1 \text{ if } M_{\theta,d}(x, y) \neq 0 \text{ and } 0 \text{ else},
\] (C.4b)
$CORL_{\theta,d} = \frac{1}{\sqrt{\sigma_x^2 \sigma_y^2}} \sum_{x=0}^{L_g-1} \sum_{y=0}^{L_g-1} (x - \mu_x)(y - \mu_y)M_{-C_{\theta,d}}(x,y)$ \hfill (C.5a)

with

$$\mu_x = \sum_{x=0}^{L_g-1} \sum_{y=0}^{L_g-1} M_c(x,y)$$ \hfill (C.5b)

and

$$\sigma_x^2 = \sum_{x=0}^{L_g-1} (x - \mu_x) \sum_{y=0}^{L_g-1} M_c(x,y),$$ \hfill (C.5c)

$$KAP_{\theta,d} = \frac{P_0 - P_c}{P_m - P_c}$$ \hfill (C.6a)

with

$$P_0 = \sum_{x=0}^{L_g-1} M_{-C_{\theta,d}}(x,x),$$ \hfill (C.6b)

$$P_c = \sum_{x=0}^{L_g-1} \sum_{y=0}^{L_g-1} M_{-C_{\theta,d}}(x,y)M_{-C_{\theta,d}}(y,x),$$ \hfill (C.6c)

$$P_m = \sum_{x=0}^{L_g-1} \min \left\{ \sum_{y=0}^{L_g-1} M_{-C_{\theta,d}}(x,y), \sum_{y=0}^{L_g-1} M_{-C_{\theta,d}}(y,x) \right\}.$$ \hfill (C.6d)

References


