Simple Algorithm to Extract Significant Echoes from Ultrasonographic Data Taken for Arterial Stiffness Measurement

[1]Ashwin K Vijayan, [2]Mohammed Ajmal C, [3]Nandakishore S
Department of Electrical Engineering,
Indian Institute of Technology Madras, Chennai, Tamil Nadu, India

***Abstract*—Arterial stiffness index is a decisive parameter on the cardiac health of a person and can be measured to achieve early detection of coronary heart disease. Imageless portable systems for automated estimation of arterial stiffness by utilizing an ultrasound transducer are gaining popularity. The arterial stiffness is found out based on the distensions of carotid artery [1]. We present an innovative signal processing algorithm for the removal of insignificant echoes in the ultrasonographic data obtained for arterial stiffness measurement. This algorithm analyzes each frame on-the-fly, segments the frame into windows and then process them. This algorithm removes echoes till and including the anechoic region by analyzing the number of strong echoes in each window. The echoes between the artery walls are also removed. Application of these algorithms on real-life data proves its efficacy with a success rate over 96%.**

***Keywords*—anechoic region, arterial stiffness, carotid artery, threshold enumeration**.

I. INTRODUCTION

Arterial stiffness and its relation to cardiovascular diseases has been a recent area of study in the biomedical domain. It is found that the abnormal stiffness of artery is an indication of cardiovascular diseases [2]. Arterial stiffness can be estimated using different techniques. The use of ultrasound to determine the arterial stiffness, particularly that of carotid artery has recently emerged as an innovative method and is gaining popularity [3]. The removal of unwanted echoes in the ultrasonographic data is an essential step and is prior to all other processing.

In this paper, we present an algorithm which removes unwanted echoes from such data. Till now, different methods have been developed for this. [4−6] discussed about the conventional variance/standard deviation based methods. The strength of such methods depend on the number of frames used for computing variance as reliability of variance depend on the number of data points used for variance calculation. More the number of frames used, more reliable the result would be. Other popular methods based on wavelet transform [7−9], energy [10−12], filtering [13], higher order statistics [14], artificial neural networks [15], probability models and associated functions [16,17] etc. have been developed. All of these are computationally tedious compared to the algorithm presented here.

II. BACKGROUND

Fully automated systems for imageless evaluation of arterial compliance are being designed [18]. In such systems, a transducer in pulse-echo mode is placed on the patient's neck (Fig. 1).

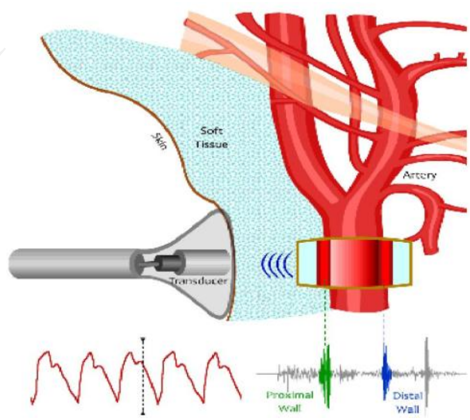

Fig. 1: Schematic of an automated system for arterial stiffness measurement. [19]

For all the trials in [18], the echo received is digitized at 100 MS/s with a pulse repetition time of 10 ms and stored in a row matrix ($1 \times N$). With M pulses sent, a matrix R (called as data matrix) of size $M \times N$ is obtained. The value of N is determined by keeping the constraint that artery wall should lie within those many data points. So, an upper bound for N is defined and data points beyond this are neglected so that the matrix size can be reduced. Each row is synonymously mentioned as frames henceforth.

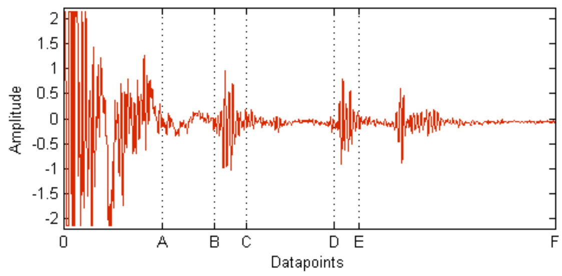

Fig. 2: A sample frame.

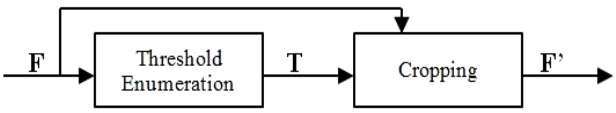

Fig. 3:Block diagram of TE algorithm.

Fig. 2 is a sample frame obtained using the system designed in [18]. In the beginning of every frame, there are high amplitude spikes due to echoes from the skin, skin-gel interface etc. These are followed by echoes from the soft tissue lying in between the skin and the first artery. This region is referred to as anechoic region. In Fig. 2, following regions can be identified.

1. The echoes from beginning till A : echoes from the skin, skin-gel interface etc.
2. The echoes between A and B : anechoic region
3. The echoes between B and C : echoes from the proximal wall of the carotid artery
4. The echoes between C and D : echoes from the distal wall of the carotid artery
5. The peaks seen after E : echoes from jugular vein

The removal of unwanted echoes in the signal is a crucial step as that makes the further analysis of the signal for determining the peaks and ultimately the arterial stiffness much simpler.

III. THRESHOLD ENUMERATION (TE) ALGORITHM

We present an extremely simple and efficient signal processing algorithm called as threshold enumeration (TE) algorithm to remove the insignificant echoes i.e., the echoes till the first artery and echoes between the artery walls. The algorithm is tested using Matlab® on real world signals obtained using the acquisition device and the settings mentioned in [18] from different test subjects.

The core principle of TE method is to estimate the position of the low echo region and trim the signal accordingly. The nature of anechoic region and the echoes between artery walls that are crucial to this method are:

1. The amplitude of echoes in anechoic region is very low compared to the artery echoes.
2. These regions span over at least a few hundred data points in each frame.

The algorithm operates on each frame on-the-fly and outputs it for further processing after removing the insignificant echoes. Fig. 3 shows the block diagram of the TE method. The inputs and outputs of each phase are mentioned in the diagram and explained in later sections.

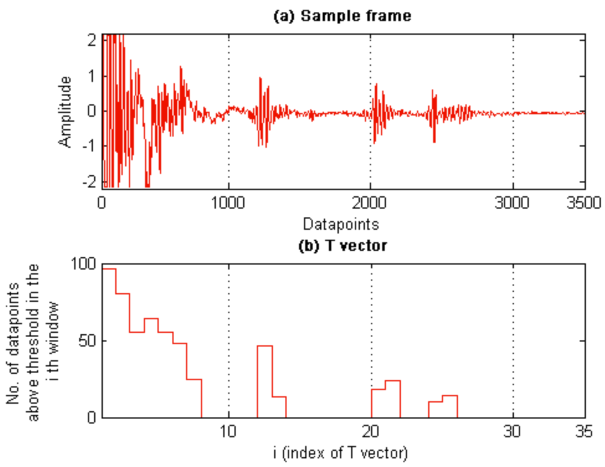

Fig. 4: A sample frame and corresponding T vector.

A. *Threshold Enumeration*

The input to the algorithm is a single frame *F* (row vector of size $1\times N$). A zero vector *T* of length $[N/l]$ ([.] represents the greatest integer function, l is the length of window) is created. This vector is used to store the number of points above a threshold value. A window W of length l is moved over *F*. Let the variable that controls the movement of the window be i. The window is defined from $i\times l$ to $(i+1)\times l-1$. In the first iteration, i will take the value 0. Therefore in the first iteration, if l is taken as 100, the window is from 0 to 99. The number of points inside W for which the echo amplitude is above a threshold is calculated and is stored at $T(i)$. i is incremented by 1 after each iteration (Fig. 4).

The conclusions that can be drawn from the plot of vector *T* are:

1. Number of datapoints above defined threshold amplitude is very large for the echoes from the skin.
2. This is followed by a region where number of datapoints above a threshold amplitude is zero. This region corresponds to the anechoic region.
3. Then it again increases when the window overlaps with the significant echoes (arteries or static echoes) and is zero for the region in between the artery walls.

With the *T* vector representing the number of data points in a window above threshold over the entire frame *F*, another iteration is set up to remove the unwanted echoes.

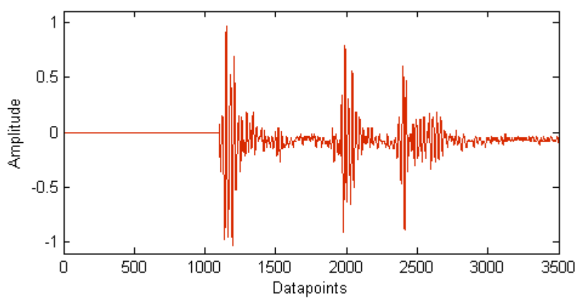

Fig. 5: A sample frame after first stage of processing.

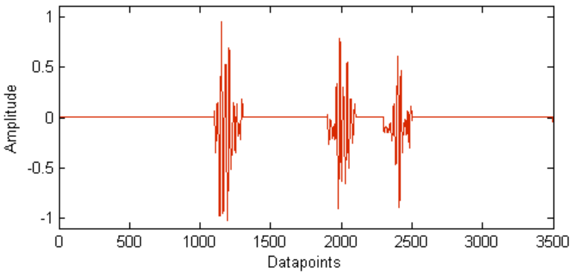

Fig. 6: A sample frame after complete processing.

B. *Cropping till the first significant echo*

To remove the echoes till the first important echo, i.e. till the artery wall, the algorithm looks for the point in T where the value is non-zero for a vector index and zero for the preceding index. All echoes in F from index 1 to index $(i-1)\times l$ are set to zero if all the following conditions are met.

1. $T(i)$ is greater than zero.
2. $T(i-1)$ is equal to zero.

These conditions are always satisfied at the first significant echoes after the anechoic region. Therefore all the echoes from beginning till the first significant echo can be cropped. But cropping is done till point $(i-1)\times l$ rather than $i\times l$ so as to trim only considerable number of data points before the first significant echo. This ensures that no required echo is missed. When the first significant echo is reached, the iteration is terminated and the echoes before the significant echo are trimmed as mentioned before (Fig. 5).

C. *Cropping the echoes between artery walls*

The same method can be used to remove the echoes between artery walls assuming that there are sufficient data points between the artery walls. Here again another loop is implemented to control the window movement. Now the new control variable j will have the initial value i. Here again the number of points under the window for which the echo amplitude is higher than the threshold is obtained from the vector T. The condition for trimming is slightly modified as follows:

1. $T(j)$ is equal to zero.
2. $T(j+1)$ is equal to zero.

This condition is true between two significant echoes and all the points from $j\times l$ to $(j+1)\times l$ of F are set to zero. When the next significant echo is reached this condition fails. Hence this method removes all the echoes between the significant echoes ensuring that none of the significant echoes are removed. The processed frame after both the cropping steps will have only the significant echoes of F (Fig. 6).

IV. PERFORMANCE AND VALIDATION

To analyze the performance of the algorithm, real-life data taken from different volunteers were processed to estimate how effectively the algorithm removes the unwanted echoes. For validating this method, we investigated the algorithm's efficiency in the following two ways.

A. *Validation using hit ratio*

The effectiveness is quantitatively evaluated by checking the number of frames where the algorithm effectively removes the unwanted echoes keeping the desired echoes untouched. The hit ratio is calculated as number of frames where this happens out of the total number of frames.

The index of the first non-zero value of the processed matrix is found out. If the algorithm is able to crop the frame in a 300 data point window around the starting of the first artery, the algorithm is said to have worked correctly or in other words, it is a hit. The number of frames for which this happens is evaluated. The results are tabulated (Table I). Each subject data has 400 frames in total.

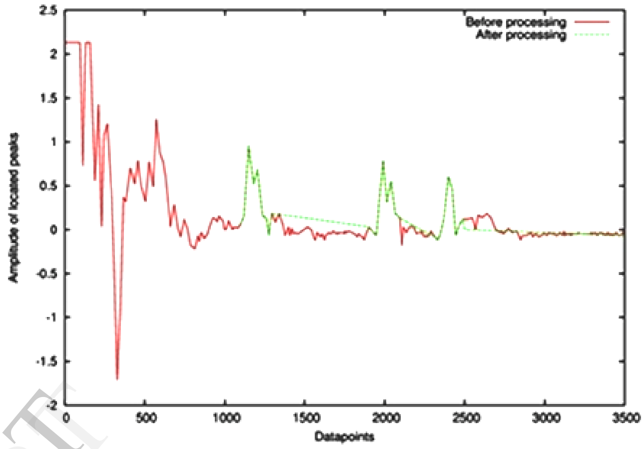

Figure 7: Peak location before and after processing.

Each of the cases where the algorithm fails to give a hit was evaluated separately to check if we are missing a required artery. It was found that in all these cases, the algorithm only crops the frame earlier in the anechoic region but do not remove any significant data. Even in these cases, skin echoes and a large part of the anechoic region as well as the non-echoic regions between arteries are removed. So, the algorithm is very reliable.

TABLE I. RESULTS OF TE ALGORITHM

Subject	No. of Hits	Hit Ratio
1	398	99.5%
2	394	98.5%
3	398	99.5%
4	384	96%
5	399	99.75%
6	396	99%
7	398	99.5%
8	391	97.75%
9	387	96.75%
10	400	100%
11	389	97.25%
12	398	99.5%
13	398	99.5%
14	387	96.75%
15	396	99%

B. Improvement in peak detection

As the removal of unwanted echoes is a prelude to the methods for peak detection, the amount by which these echoes are removed improves the ease of peak detection. This is calculated by performing peak detection on the raw data as well as the processed data. The number of peaks in each case along with the plots clearly indicates the usefulness of the algorithm (Fig. 7)

V. CONCLUSION

In this paper, we have discussed an efficient method called as threshold enumeration(TE) method to remove the unwanted echoes from given ultrasonographic data taken for arterial stiffness measurement. This algorithm enumerates the number of high threshold values in a window and removes the unwanted echoes using this. The ability of the algorithm to effectively remove the unwanted echoes across the different subjects is observed through plots, hit ratio and improvement in peak detection. The algorithm removes the anechoic region as well as the low amplitude echo portion between the arteries effectively, thereby improving ease of peak detection. Using the various ultrasonographic data specimens, the efficiency and accuracy of this method is evaluated and demonstrated. It is found that this algorithm takes only 2-4% of time that is required for a variance based method.

ACKNOWLEDGMENT

The authors would like to thank Healthcare Technology Innovation Centre (HTIC), Chennai, India for giving the ultrasonographic data obtained from different test subjects to validate the efficacy of the algorithm. They also thank Preethi Gopal of HTIC for all the support and guidance.

REFERENCES

[1] Jacques Blacher, Bruno Pannier, Alain P. Guerin, et. al, "Carotid arterial stiffness as a predictor of cardiovascular and all-cause mortality in end-stage renal disease," Hypertension, vol. 32, pp. 570-574, 1998
[2] Sheng Kang, Hui-Min Fan, Jue Li, Lie-Ying Fan, et. al, "Relationship of arterial stiffness and early mild diastolic heart failure in general middle and aged population," European Heart Journal, vol. 31, pp. 2799–2807,2010.
[3] Selzer R. H., Mack W. J., Lee P. L., Kwong-Fu H., and Hodis H. N., "Improved common carotid elasticity and intima-media thickness measurements from computer analysis of sequential ultrasound frames," Atherosclerosis, vol. 154, pp. 185–193, Jan 2001.
[4] Mark A. Espeland, Timothy E. Craven, Ward A. Riley, John Corson, Alicia Romont, and Curt D. Furberg, "Reliability of longitudinal ultrasonographic measurements of carotid intimal-medial thicknesses," Stroke, vol. 27, pp. 480-485, 1996.
[5] Luca Saba, Giorgio Mallarini, Roberto Sanfilippo, Guang Zeng, Roberto Montisci, and Jasjit Suri, "Intima media thickness variability (imtv) and its association with cerebrovascular events: a novel marker of carotid atherosclerosis?," Cardiovascular Diagnosis and Therapy, vol. 2, no. 1, pp. 10–18, Mar 2012.
[6] Asmatullah Chaudhry, Mehdi Hassan, Asifullah Khan, and Jin Young Kim, "Automatic active contour-based segmentation and classification of carotid artery ultrasound images," Journal of Digital Imaging, vol. 26, no. 6, pp. 1071-1081, Dec. 2013.
[7] Angrisani L., Daponte P., and D'Apuzzo M., "Detection of echoes from the multilayer structures by using the wavelet transform," IEEE Trans. on Instrumentation and Measurement, vol. 49 , no. 4, pp. 727 - 731, Aug 2000.
[8] Shubha Kadambe, Robin Murray, and G. Faye Boudreaux-Bartels, "Wavelet transform-based qrs complex detector," IEEE Trans. On Biomedical Engineering, vol. 46 , no. 7, pp. 838-848, July 1999.
[9] Du P., Kibbe W. A., and Lin S. M., "Improved peak detection in mass spectrum by incorporating continuous wavelet transform-based pattern matching," Bioinformatics, vol. 22, no. 17, pp. 2059-65, Sep 2006.
[10] Ukwatta E., Awad J., Ward A. D., and Buchanan D., "Coupled level set approach to segment carotid arteries from 3d ultrasound image," 2011 IEEE International Symposium on Biomedical Imaging: From Nano to Macro, pp. 37 - 40.
[11] Alessandro C. Rossiemail, Peter J. Brandsemail, and Arnold P.G. Hoeks, "Automatic localization of intimal and adventitial carotid artery layers with noninvasive ultrasound: a novel algorithm providing scan quality control," Ultrasound in Medicine and Biology, vol. 36, no. 3, pp. 467-479, March 2010.
[12] Ukwatta E., Awad J., Ward A. D., Buchanan D., Samarabandu J., Parraga G., and Fenster A., "Three-dimensional ultrasound of carotid atherosclerosis: semiautomated segmentation using a level set-based method," Medical Physics, vol. 38, no. 5, pp. 2479-93, May 2011.
[13] Mattias J. Fredriksson, Patrik Petersson, Bengt-Olof Axelsson, and Dan Bylund, "An automatic peak finding method for lcms data using gaussian second derivative filtering," Journal of Separation Science, vol. 32, no. 22, pp-3906-18, Oct 2009.
[14] K. I. Panoulas, L. J. Hadjileontiadis, and S. M. Panas, "Enhancement of R-wave detection in ECG data analysis using higher-order statistics," in Proc. of the 23rd Annual International Conference of the IEEE:Engineering in Medicine and Biology Society, vol. 1, 2001.
[15] V. R. Newey and D. K. Nassiri, "Online artery diameter measurement in ultrasound images using artificial neural networks," Ultrasound in Medicine and Biology, vol. 28, no. 2, pp. 209–216, 2002.
[16] G. Mendizabal-Ruiz, M. Rivera, and I. A. Kakadiaris, "A probabilistic segmentation method for the identification of luminal borders in intravascular ultrasound images," in Proc. of the 26th IEEE Conference on Computer Vision and Pattern Recognition, pp. 1–8, 2008.
[17] Baris Kanber and Kumar Vids Ramnarine, "A probabilistic approach to computerized tracking of arterial walls in ultrasound image sequences," International Scholarly Research Network:Signal Processing, vol. 2012, Article ID 179087.
[18] Ashish Kumar Sahani, Jayaraj Joseph, and Mohanasankar Sivaprakasam, "Automated system for imageless evaluation of arterial compliance," 34th Annual International Conference of the IEEE EMBS, pp. 227 - 231.
[19] http://htic.iitm.ac.in/?q=artsens, accessed on Jun 11, 2014.