MOTION ARTIFACT ELIMINATION ALGORITHM AND ARCHITECTURE FOR EIGEN-BASED CLUTTER FILTER IN COLOR DOPPLER PROCESSING


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ABSTRACT

Color Doppler imaging is used to visualize the distribution of blood flow in the region of interest. Slight relative motion causes severe image corruption and incorrect blood velocity estimation. In this work, we propose a velocity bias cancellation algorithm based on the autocorrelation technique, which is widely used in color Doppler to eliminate the motion artifact. The proposed algorithm can assist clutter filter in suppressing tissue noise effectively while compensating for the biased velocity. The proposed algorithm enhances the performance around 3-9 dB in Signal-to-Clutter Ratio (SCR), and reduces the error of blood velocity estimation by around 69%. Besides, we propose the rearrangement scheme to increase the throughput by reducing the average number of computed eigen-components from 8 to only 2.35. The proposed velocity bias cancellation algorithm and the rearrangement scheme are implemented in TSMC CMOS 90nm technology. The area and maximum operation frequency are 3.39 mm² and 100 MHz, respectively.

Key words: Color Doppler, Motion artifact, Ultrasound, VLSI.

I. INTRODUCTION

Color Doppler imaging is important in medical ultrasounds, used to visualize the distribution of blood flow in the region of interest. However, color Doppler imaging often suffers from the motion between the probe and the patients; moreover, the computational complexity of color Doppler imaging is extremely high.

As shown in Fig. 1(b), slight motion between the probe and target, caused by tissue motion, respiration, body and probe movements, can lead to severe image corruption and incorrect blood velocity bias. Therefore, patients are asked to hold their breath to reduce the relative motion. However, it is difficult to request children and unconscious patients to suspend their breathing. Furthermore, motion cannot be avoided in an emergency situation, such as in a moving ambulance.

To suppress the clutter noises with motion artifact, eigen-based clutter filter was proposed [1]-[4] to adapt the passband and stopband for the moving tissue. In order to address the clutter noise accurately, the authors in [2] use the mean frequency of dominant eigen-component as the center frequency of clutter noise. Nevertheless, it is unsuitable under low clutter-to-blood ratio (CBR), because the blood information may be eliminated instead of clutter noise. Moreover, the high computational complexity of the eigen-based clutter filter is still the main limitation for real-time Doppler flow imaging.

Fig. 1 (a) Normal image, and (b) motion-corrupted image.
In this paper, we propose a velocity bias cancellation algorithm and an architecture based on eigen-based clutter filter to improve the correctness of motion estimation. The proposed algorithm includes weighted autocorrelation, frequency threshold adjustment, and velocity compensation. Moreover, we propose a rearrangement scheme to increase the throughput by reducing the average number of computed eigen-components from 8 to only 2.35. Lastly, we implement the proposed color Doppler DSP engine in TSMC CMOS 90nm technology. The core size is 3.39 mm² at 100MHz operating frequency.

This paper is organized as follows: The color Doppler imaging algorithms are described in Section II; The proposed velocity bias cancellation algorithm is shown in Section III; the simulation results and comparisons are presented in Section IV; While in Section V, we describe our architecture design and our proposed rearrangement scheme. The implementation results and conclusion are presented in Sections VI and VII, respectively.

II. COLOR DOPPLER IMAGING

In order to obtain color flow images, several mechanisms are applied in the color Doppler processing to suppress different types of noises. The traditional block diagram of the color Doppler processing is shown in Fig. 2. Complex data after beamforming are fed into the color Doppler engine, and velocity, energy and variance of blood flow signal are computed as outputs. In this traditional block diagram, all blocks are designed for suppressing noises and improving image quality except that the flow parameter estimation is for deriving the required flow parameters. Besides, the clutter filter and image filter we adopt in this work have the adaptability with different environment. In the following sections, the detailed description of the functional blocks will be illustrated.

A. Joint-decision Eigen-based Clutter filter

To eliminate clutter noise efficiently, we adopt a joint-decision algorithm clutter filter [10] in this work. Unlike conventional clutter filters, which identify clutter noise by either frequency-based or eigen-based algorithm, the joint-decision algorithm separates clutter noises and blood signals in both eigen-domain and frequency-domain. Therefore, the chance of misidentify is reduced and more blood signals is preserved while removing clutter noises.

The general filter can be modeled by a matrix-vector multiplication as:

\[ y = Ax, \]

where \( x \) is the input signal vector, \( A \) is the clutter filter matrix, and \( y \) is the filtered signal vector. The eigen-based clutter filter can adapt the characteristics of clutter signal as a regression filter which can be written as:

\[ A = I - \sum_{i=1}^{K} e_i e_i^H, \]

where the set of \( e_i \) is an orthonormal basis for the clutter noise space, \( K \) is the clutter space order, and \( ()^H \) indicates the Hermitian operation. We will illustrate how to determine the clutter noise \( e_i \) using proposed joint-decision algorithm in the next paragraph. By subtracting the signal component contained in the clutter space, the filter matrix \( A \) can project the input signal vector \( x \) into the blood signal space which is orthogonal to the clutter space.

The joint-decision algorithm has two criterion, eigen-based criterion and frequency-based criterion. The eigen-based criterion is based on the property that the clutter energy is typically 20~70 dB greater than the blood flow energy, the clutter energy concentrating in few eigen-components. Therefore, if the ratio of eigen-values of adjacent eigen-components is larger than a pre-defined threshold \( r th \), the previous eigen-component is regarded as clutter noise and gathered in the clutter space \( \Phi_c \).

\[ \Phi_c = \{ e_i | \frac{\lambda_i}{\lambda_{i+1}} \geq r_{th} \}, i = 1, \cdots, N \]

The frequency-based criterion is based on the fact that the velocity of tissue region is relatively smaller than the velocity of blood flow region, thus an eigen-component with frequency belows a pre-defined threshold \( f_{th} \) is identified as clutter noise. To avoid over-threshold and under-threshold problems, we normalize the frequency to the mean frequency of all eigen-components \( f_i \). And the criterion is described as:

\[ \Phi_c = \{ e_i | |f_i - f_{th}| \leq r_{th} \}, i = 1, \cdots, N \]

where the frequency \( f_i \) of each eigenvector \( e_i \) can be calculated by lag-one autocorrelation [6]:

\[ f_i = \frac{1}{2\pi T} \left( \sum_{n=0}^{N} e_i(n)e_i(n+1) \right), \]

where \( T \) is the pulse repetition interval, \( \angle \) represents the phase and \( * \) denotes the complex conjugate.
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B. Thresholding

The primary goal of the thresholding is to remove the remaining undesired noises from the filtered signals. For example, since white noises have the property of both high frequency and low energy, it cannot be removed by the clutter filter. Hence, a fixed energy threshold is often used to remove the remaining noises. When the eliminated clutter energy of a pixel is higher than the threshold, the pixel is regarded as tissue region and the remaining signals are noises.

C. Flow Estimation

For a basic color Doppler processor, the autocorrelation techniques, which have been adopted into this work, are widely utilized to calculate the flow parameters [6]. For each Doppler signal \( S(i, T) \) received from a particular gate, the first lag and zero lag of its autocorrelation function are listed as follows:

\[
\hat{R}(T) = \frac{1}{N-1} \sum_{i=1}^{N} S((i+1) \cdot T) S^*(i \cdot T),
\]

\[
\hat{R}(0) = \frac{1}{N} \sum_{i=1}^{N} S(i \cdot T) S^*(i \cdot T).
\]

Then the three main flow parameters: mean velocity, \( \bar{v} \), variance, \( \sigma^2 \), and energy, \( E \), can be calculated as:

\[
\bar{v} = \frac{\lambda}{4\pi} \hat{R}(T),
\]

\[
\sigma^2 = \frac{2}{T^2} \left( 1 - \frac{\hat{R}(T)}{\hat{R}(0)} \right),
\]

\[
E = \hat{R}(0),
\]

where \( \lambda \) is the acoustic wave length.

D. Persistence

Persistence accomplishes temporal averaging by filtering image pixels at the same location of successive frames. Hence, a great deal of memory is required to buffer frames. In order to reduce the cost of frame buffers and to simplify the parameter setting, we employ a forgetting factor \( \alpha \) to obtain the new average from the previous average and the pixel value:

\[
\text{Avg}_i(m,n) = \alpha \cdot \text{Avg}_{i-1}(m,n) + (1 - \alpha) \cdot P_i(m,n), \quad 0 \leq \alpha < 1.
\]

where \( i \) presents the \( i \)th frame, \( P_i(m,n) \) means the value in pixel \( (m,n) \), and \( \text{Avg}_i(m,n) \) means the average of successive frames in pixel \( (m,n) \). The above equation can be seen as the infinite impulse response (IIR) filter in the successive frames. As a result, we only need to buffer the previous average and the required size of buffer is reduced to one frame.

E. Image Filter

The image filter takes spatial filtering to eliminate salt-and-pepper noises and background noises. In addition to noise suppression, preserving useful information such as anatomical boundaries in an image is also important to spatial-domain filter. Besides, considering the characteristic of color Doppler images, we adopt the adaptive-size median filter [11] in this work.

III. PROPOSED VELOCITY BIAS CANCELLATION ALGORITHM

In this section, we propose a velocity bias cancellation algorithm based on an eigen-based clutter filter. We assume the relative motion is in the same direction. The proposed algorithm includes three steps in three different blocks, depicted in yellow, as shown in Fig. 3. First, velocity bias, caused by motion artifact, is calculated in the biased velocity estimation. Second, the frequency threshold in eigen-based clutter is adjusted with the velocity bias and the variance of the estimated velocity. Finally, the biased blood velocity is compensated by the velocity bias to get the correct velocity in flow parameter estimation. The proposed velocity bias cancellation algorithm can effectively assist the eigen-based clutter filter to eliminate moving tissue and compensate the biased blood velocity.

A. Biased Velocity Estimation

Several motion compensation algorithms utilize cross correlation of pixels to estimate the value of motion artifacts, which is called velocity bias in this work [7][8]. However, cross correlation is not suitable for color Doppler due to the decimation of RF data. The input data of Doppler processing are baseband signals with low sampling rate. Therefore, the size each pixel representing increases. As shown in Fig. 4(a), when the cross correlation technique is utilized, the displacement of two frames is likely to be computed incorrectly since the displacement is less than the size that a pixel represents.

Fig. 3  Block diagram of the color Doppler processing with proposed velocity bias cancellation algorithm.
In order to improve the correctness of biased velocity estimation, we propose the weighted autocorrelation method. Autocorrelation technique [6] is widely used in color Doppler to calculate the flow parameter, such as velocity, and energy. Since autocorrelation technique computes the phase difference between frames, it is not affected by the size that each pixel represents. The autocorrelation and frequency of slow-time signal \( X \) in pixel \((m, n)\) can be represented, respectively, as follows:

\[
\hat{R}_{m,n}(T) = \frac{1}{N-1} \sum_{i=1}^{N-1} X((i+1)\cdot T)X^*(i\cdot T),
\]

\[
\hat{f}_{m,n} = \frac{\hat{R}_{m,n}(T)}{2\pi T}.
\]

Moreover, in order to avoid the influence of blood velocity, we regard energy as weight to calculate the average frequency bias because the energy of tissue signal is typically 40-80dB stronger than the one of blood signal. And the center frequency \( f_c \) of tissue in (5), which will be called frequency bias \( f_b \) in this work, is revised and represented as following:

\[
f_b = \frac{1}{\sum_{m=1}^{M} \sum_{n=1}^{N} E_{m,n}} \sum_{m=1}^{M} \sum_{n=1}^{N} E_{m,n} \cdot \hat{f}_{m,n},
\]

where \( E_{m,n} \) is the energy of slow-time signal \( X \) in pixel \((m, n)\), which is written as

\[
E_{m,n} = \frac{1}{N} \sum_{i=1}^{N} X(i\cdot T)X^*(i\cdot T).
\]

And the velocity bias \( V_b \) can be calculated from the frequency bias, which is written as

\[
V_b = \frac{c}{2f_c} f_b.
\]

where \( c \) is the sound velocity.

**B. Frequency-threshold Adjusting in Clutter Filter**

In this step, the frequency threshold in (5) will be adjusted by the distribution of estimated velocity. To observe the distribution of estimated velocity in moving tissue, we use the Field II [9] program to generate synthetic data with different probe velocities. The direction of motion is divided into axial and lateral motion. Axial motion is the motion where the probe moves toward or away the target, while the lateral motion is in the direction perpendicular to the axial motion.

With different velocities of probe, we can obtain the mean and standard deviation of velocity estimated by autocorrelation technique for tissue part. As shown in Fig. 5, the blue line represents the data with only axial probe motion from 0.02 m/s to 0.2 m/s, while the red line represents the data with axial probe motion from 0.02 m/s to 0.2 m/s upward and lateral probe motion from 0.01 m/s to 0.1 m/s rightward, representing half the value of corresponding axial motion. We find that the standard deviation increases mainly with the mean of estimated velocity in axial motion. Besides, a proximate linear relationship exists between the mean and the standard deviation of estimated velocity. In other words, a linear function of the green line shown in Fig. 5 could be utilized to describe their relationship. This means that when the mean velocity is known, its approximate standard deviation can be calculated.

Moreover, we observe the velocity distribution under different axial velocities as shown in Fig. 6. The velocity distribution can be mapped into symmetrical exponential distributions in which more than 95% of values are within 3 standard deviations. That is, the frequency threshold in eigen-based clutter filter can be adjusted for the mean and standard deviation of the estimated velocity bias to eliminate the clutter noise caused by moving tissue. Thus, (5) can be revised and rewritten as

\[
R_{m,n}(T) = \frac{1}{N-1} \sum_{i=1}^{N-1} X((i+1)\cdot T)X^*(i\cdot T),
\]

\[
\hat{f}_{m,n} = \frac{\hat{R}_{m,n}(T)}{2\pi T}.
\]

\[
\hat{f}_{m,n} = \frac{\hat{R}_{m,n}(T)}{2\pi T}.
\]
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Fig. 6 Velocity distributions under different velocities of motion artifact.

\[ \Phi = \left\{ e_{k} \mid f_{k} - f_{b} < (f_{b} + 3\sigma_{v}) \right\}, \quad (17) \]

where \( \sigma_{v} \) is the standard deviation of velocity distribution. Therefore, we can suppress more clutter noise caused by moving tissue, thus adjusting the frequency threshold.

C. Velocity Compensation

Since the blood velocity is biased by the motion artifact, it should be compensated with the velocity bias in the flow parameter estimation block to get the correct estimated velocity. The velocity bias \( V_{b} \) can be calculated from the frequency bias, which is written as

\[ V_{b} = \frac{c}{2f_{c}} f_{b} \quad (18) \]

We can obtain the correct estimated velocity \( V_{\text{correct}} \) by compensating the original estimated velocity \( V_{\text{origin}} \) with \( V_{b} \) as follow,

\[ V_{\text{correct}} = V_{\text{origin}} - V_{b} \quad (19) \]

IV. SIMULATION RESULTS AND COMPARISONS

Since general medical ultrasound images are hard to know the velocity bias and the accurate blood velocity, conventional metrics can’t be used to measure the quality after filtering implementation. Therefore, we use the Field II [9] program to generate synthetic data to evaluate the performance. The color Doppler imaging without motion artifact is taken to be the golden pattern, shown in Fig. 7, and our simulation parameters are given in Table 1. For quantitative evaluation, two parameters are utilized. One is the signal-to-clutter ratio (SCR) [9], which is used to evaluate the effectiveness of clutter rejection. And the other is the Blood Velocity Difference (BVD), which is used to evaluate the accuracy of velocity compensation. Its definition is depicted as

\[ BVD = \frac{\sum_{m,n} |V_{\text{NoMotion}} - V_{\text{Compensate}}|}{M \cdot N} \quad (20) \]

where \( V_{\text{NoMotion}} \) is the estimated velocity of the golden pattern, and \( V_{\text{Compensate}} \) is the velocity after compensation under motion environment.

The simulation results are shown in Fig. 8 and Fig. 9, respectively. As depicted in Fig. 8, the clutter filter fails to suppress the clutter noise with fixed frequency thresholding. Most of the tissue signals are regarded as blood signals with velocity around -0.06 m/s due to the probe velocity. Although dynamic frequency thresholding eliminates additional clutter noise, it results in loss of blood information as well. However, by applying the proposed method, most of the tissue signals can be eliminated effectively and the blood velocity estimation is similar with the one without motion artifact in Fig. 7. Besides, as shown in Fig. 9, compared with the reference works, the proposed algorithm increases SCR about 3-9

<table>
<thead>
<tr>
<th>Table 1  Field II simulation parameters.</th>
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<tbody>
<tr>
<td>Simulated part</td>
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<tr>
<td>----------------</td>
</tr>
<tr>
<td>Ensemble Number</td>
</tr>
<tr>
<td>Sound velocity</td>
</tr>
<tr>
<td>Center freq.</td>
</tr>
<tr>
<td>Pulse repetition freq.</td>
</tr>
<tr>
<td>Radius of vessel</td>
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<tr>
<td>Hear rate</td>
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<tr>
<td>Mean velocity of blood</td>
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<tr>
<td>Axial probe velocity</td>
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</table>

Fig. 7 Color Doppler images without probe motion (a) velocity, (b) energy, (c) variance.
V. ARCHITECTURAL DESIGN

In this section, we introduce the architectural design of the proposed color Doppler engine. As shown in Fig. 10, we only implement the core blocks of the proposed color Doppler engine because the VLSI implementation of image filters such as median filters are well discussed in other works. Since the proposed color Doppler engine is a feed-forward system, the system can be implemented by mapping the blocks directly. However, the throughput of the direct implementation is low because the eigen-based clutter filter has a long latency. Therefore, we first introduce the direct implementation of the color Doppler engine. Then, we discuss the proposed rearrangement scheme which can reduce the latency significantly by using the property of the clutter filter and thresholding algorithm.

A. Direct Implementation

Since the biased velocity estimation block is designed based on autocorrelation techniques, the architecture of biased velocity estimation is similar to the architecture of flow parameter estimation. Therefore, we introduce these two architectures together. Fig. 11 and Fig. 12 show the architectures of biased velocity estimation and flow parameter estimation, respectively. Since both require calculating the velocity and energy by using autocorrelation technique, part of the architecture and hardware can be shared to reduce the area cost. The sharing part is depicted by the blue dotted line in Fig. 12.

The architecture of the eigen-based clutter filter and adaptive energy thresholding is shown in Fig. 13. It is mainly composed of five parts: 1) calculate autocorrelation matrix R; 2) perform SVD by super-linear SVD algorithm (SL-SVD) [19]; 3) determine the clutter space order using joint-decision algorithm; 4) calculate filtered signal; and 5) use adaptive energy thresholding. The most complex part of the architecture in Fig. 13 is the SVD part. To obtain the eigen-pair in eigen-based clutter filter efficiently, we use the super-linear SVD algorithm (SL-SVD) [19], which has lower complexity and higher throughput than other works [17]-[19]. Although we use the SL-SVD algorithm, the latency of the direct implementation is still too high. Hence, we propose a rearrangement scheme to increase the throughput in the following section.

Fig. 8 Color Doppler images with probe velocity 0.06 m/s upward (a) velocity, (b) energy, (c) variance.

Fig. 9 (a) SCR, (b) BVD of different algorithms used in joint-decision algorithm under different axial probe velocities.

dB and reduces the error of blood velocity estimation by more than 69%.
B. Rearrangement Scheme

Based on ensemble number in Table 2, we should perform SVD on a square complex matrix from size $5 \times 5$ to size $8 \times 8$ [2]. Large matrix size leads to high computational complexity and slow convergence rate when performing SVD. Since the goal of clutter filter is to find the clutter space, we only have to derive the eigen-components belonging to the clutter space instead of all of them. Therefore, we design a rearrangement scheme for complexity reduction by rearranging the order of the joint-decision algorithm and adaptive energy thresholding to reduce the overall iteration number of the SL-SVD algorithm. The concept of a rearrangement scheme is shown in Fig. 15.

The eigenvalue-based criterion in joint-decision algorithm compares the ratio of two adjacent eigenvalues to a threshold until the ratio is smaller than or equal to the threshold. Next, the derived eigen-components are examined by the frequency-based criterion to identify whether they are clutter or not. Furthermore, we also use the property of adaptive energy thresholding to eliminate the redundant computation. The adaptive energy thresholding determines whether a pixel belongs to tissue or blood by the eliminated clutter power ratio (CPR) [20], the ratio of the clutter energy to the overall energy of the pixel. Since the eigenvalues are non-negative, the CPR is monotonically increasing when a new eigen-component is derived. Once the CPR reaches the expected clutter power ratio (ECPR) [20], the pixel belongs to tissue and the iteration of SVD can be stopped. Therefore, by using proposed rearrangement scheme, we can rearrange the architecture from Fig. 14 to Fig. 16.

We use the Field II program to produce synthetic data, and count the number of computed eigen-compo-

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Table 2 Adjustable parameters in the proposed color Doppler DSP engine.

<table>
<thead>
<tr>
<th>Block</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>Pixels of row</td>
</tr>
<tr>
<td></td>
<td>Pixels of column</td>
</tr>
<tr>
<td>Doppler Gate</td>
<td>Ensemble Number</td>
</tr>
<tr>
<td>Eigen-based Clutter Filter</td>
<td>Threshold values</td>
</tr>
<tr>
<td>Adaptive Energy Thresholding</td>
<td>Energy ratio threshold</td>
</tr>
</tbody>
</table>

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Fig. 13 Architecture of clutter filter and thresholding.

Fig. 14 Architecture block of Fig. 13 using direct implementation.

Fig. 15 Concept of rearrangement scheme: (a)Direct implementation, (b)Rearrangement scheme.

Fig. 16 Architecture block from eigen-based clutter filter to flow parameter estimation using proposed rearrangement scheme.

Fig. 17 Block diagram of rearrangement scheme from eigen-based clutter filter to flow parameter estimation.
Fig. 18 The Distribution of computed eigen-component number with (a) rearrangemennt using only joint-decision algorithm, and (b) proposed rearrangement scheme (using joint-decision algorithm & adaptive energy thresholding).

Table 3 Complexity evaluation of rearrangement scheme.

<table>
<thead>
<tr>
<th>SL-SVD for Matrix size 8×8</th>
<th>Direct implementation</th>
<th>rearrangement scheme using only joint-decision algorithm</th>
<th>Proposed rearrangement scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. No. of computed eig-en-components</td>
<td>8</td>
<td>3.86</td>
<td>2.35</td>
</tr>
</tbody>
</table>

Fig. 19 Chip layout of the proposed color Doppler DSP engine.

Table 4 Chip features.

<table>
<thead>
<tr>
<th>Motion-compensated Color Doppler IP</th>
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<tbody>
<tr>
<td>Cell library</td>
</tr>
<tr>
<td>TSMC 90nm</td>
</tr>
<tr>
<td>Gate count</td>
</tr>
<tr>
<td>606.5K</td>
</tr>
<tr>
<td>Core area</td>
</tr>
<tr>
<td>3.39 mm²</td>
</tr>
<tr>
<td>Max. operating freq.</td>
</tr>
<tr>
<td>100 MHz</td>
</tr>
<tr>
<td>Frame rate</td>
</tr>
<tr>
<td>33.63 frames/s</td>
</tr>
</tbody>
</table>

Compared with the referenced works, the proposed algorithm has approximately 3-9 dB better performance in SCR and the error of blood velocity estimation can be reduced by around 69%. We also propose a rearrangement scheme to increase the throughput by reducing the average number of computed eigen-components from 8 to only 2.35. Besides, we implement proposed velocity bias cancellation algorithm and rearrangement scheme by VLSI in TSMC CMOS 90nm technology. The area and maximum operation frequency of the synthesis results are 3.39 mm² and 100 MHz.

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REFERENCES


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Dr. Wu had served as the Associate Editors of leading IEEE Transactions in the circuits and systems area and signal processing area, such as IEEE TRANSACTIONS ON VERT LARGE SCALE INTEGRATION (VLSI) SYSTEMS, IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS I: REGULAR PAPERS, IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS II: EXPRESS BRIEFS, and IEEE TRANSACTIONS ON SIGNAL PROCESSING. He is now serving as the Chair of VLSI Systems and Architectures (VSA) Technical Committee in IEEE Circuits and Systems (CAS) Society. From August 2007 to Dec. 2009, he was on leave from NTU and served as the Deputy General Director of SoC Technology Center (STC), Industrial Technology Research Institute (ITRI), Hsinchu, TAIWAN, supervising Parallel Core Architecture (PAC) VLIW DSP Processor and Multicore/Android SoC platform projects. In 2010, Dr. Wu received “Outstanding EE Professor Award” from The Chinese Institute of Electrical Engineering (CIEE), Taiwan.