SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379 / https://doi.org/10.14445/23488379/IJEEE-V10I2P110

Volume 10 Issue 2, 102-109, February 2023

Original Article

Fowlkes-Mallows Correlated Cohen Kappa Coefficient Block Matching based Multi-Layer Perceptron Classification for Motion Estimation in VLSI

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Received: 07 January 2023 Revised: 07 February 2023 Accepted: 17 February 2023 Published: 28 February 2023

Abstract - *Motion Estimation (ME) constitutes an essential process in video coding with lesser processing time. Many methods were designed for efficient motion estimation in the VLSI architecture. However, the consumption of power was not reduced through existing techniques. Fowlkes–Mallows Correlated Cohen Kappa Coefficient Block Matching-based Multi-Layer Perceptron Classifier (FMCCKCBM-MLPC) Model is introduced to handle such limitations. FMCCKCBM-MLPC Model is used for increasing the motion estimation of video series in the VLSI architecture circuits. Multi-Layer Percepton is used for examining the feature and performing classification with the multiple layers. Input is sent to the hidden layer 1. In hidden layer 1, the segmentation process is performed by Fowlkes–Mallows Regularized Principal Component Regression to reduce the time loss. In hidden layer 2, the block matching is carried out by Cohen Kappa Coefficient with the segmented blocks. With Cohen Kappa Coefficient, the repeated blocks are predicted with lesser loss in the video series. This helps to enhance motion estimation in the VLSI architecture. FMCCKCBM-MLPC Model is computed in terms of power and time consumption. The simulation result of the FMCCKCBM-MLPC Model minimizes the area, PSNR, delay and power consumption of motion estimation in the video series with existing techniques.*

Keywords - *Motion estimation, Video sequence, Segmentation, Cohen kappa coefficient, Block matching.*

1. Introduction

Motion estimation is a method of identifying the vectors in the video system. It includes an entire image. The Quadrant-based search method with zero motion prejudgment was introduced in [1] to ME using HEVC. HEVC was employed to attain an efficient output using lesser time.

However, the loss rate was not minimized by the designed algorithm. Motion vector with optimization motion estimation (OME) was carried out in [2] to enhance pixel accuracy. Motion estimation with integer pixel precision was determined by determining the displacement at a finer resolution. Energy effective motion estimation method was minimized to remain frame in motion compensation. However, the computational cost was not reduced by OME.

A rectangular search pattern was employed in [3] with a diamond search pattern. The number of point searching was carried out using PSNR. However, the complexity level was not reduced by a rectangular search pattern. A two-tractable Rolling Shutter (RS) stereo model was introduced in [4] to scale the optical flow vector. The RS stereo image correction technique eliminated the RS distortion and recovered the better-quality GS.

The motion estimation technique termed Hilbert phase-based motion estimation was designed [5] depending on phase-domain image processing to identify motion accurately and efficiently [21]. However, time was not minimized using Hilbert phase-based motion estimation. LV motion estimation technique was introduced in [6] depending on sparse illustration.

A novel independent univariate GM model was designed in [7] with action recognition characteristics. GM was position invariant from universal camera motion. Ball and Volleyball Motion Estimation was introduced in [8] to identify the variance image. Optimized toss Volleyball was determined through Volleyball Motion Estimation Algorithm

AME-LWL was introduced in [9] with better-precision non-parametric modelling technology. A new 3D point cloud sequence-based algorithm was introduced in [10] to determine the rotation motion parameters—the designed algorithm comprised a double registration matrix and motion equation.

The main contribution of the FMCCKCBM-MLPC Model is as follows: FMCCKCBM-MLPC Model is used to enhance the motion estimation of video series in VLSI circuits. Multi-Layer Percepton is used for examining the feature and performing classification with multiple layers. In hidden layer 1, the segmentation process is performed through the Fowlkes–Mallows Regularized Principal Component Regression to minimize the time loss. The block matching is performed through Cohen Kappa Coefficient with segmented blocks. With Cohen Kappa Coefficient, the repeated blocks are predicted with minimal loss in video series. This helps to enhance motion estimation in the VLSI architecture.

The road map of the article is given in: section 2 provides the related works. Section 3 explains the research methodology with a neat architectural algorithm. Section 4 describes the software used with the result discussion. Section 5 explains the conclusion of the paper.

2. Related Works

A new motion tracking method was introduced in [11] with motion blur modelling and sharp object texture. An information source was employed for information about object motion during exposure. Object motion estimation technique was introduced in [12] depending on industrial image properties. A bounding box was developed for every object. ME was attained through bounding box updation with the help of expectation–maximization opinion.

Real-Time Motion Estimation was employed by [13] with GPU, FPGAs, VLSI system, DSP, and Multicores, among additional platforms. The guest editors addressed the existing problem of attaining high-performance motion estimation. A motion estimation method was introduced in [14] with US imaging. The designed method was determined with realistic simulated US images and real US sequences of the phantom.

A new framework was introduced in [26] for efficient activity recognition of daily living (ADLs) collected by static colour cameras in real-world scenarios. The framework minimized the computational cost of ADL recognition in compressed and uncompressed domains. A modified sub-pixel block matching technique was introduced by [16] to increase the accuracy of the two-dimensional motion of CCA. DAS technique was employed using a fuzzy set model was employed for computing the same blocks.

Variable Size Block Matching (VSBM) was introduced in [17] using a cross-square search pattern. VSBM minimized the error as well as the ME procedure. A supervised learning approach was designed in [18] for the fluid motion estimation problem. CNN was employed to determine the dense motion to PIV for enhancing productivity.

A cascaded architecture was introduced in [19] to ME. Image de-hazing network constructed with ResINet. The optical flow was used for determining the data. A new Single-pixel imaging (SPI) approach was designed in [20] to allow imaging scenarios. Designed approach estimated motion direction over inter-frame cross-correlation in the reconstruction model. An RNS implementation of motion estimation was designed in [27] for the latest video coding standard known as high-efficiency video coding (HEVC) or H.265. The all-direction search (ADS) pattern was developed in [22], which searches for the best block in all possible directions. A halfway stop technique was applied in the search process to improve search speed. An intelligent dynamic - voltage - frequency - scaling - aware (DVFS - aware) coding - bandwidth - efficient HEVC ME controller algorithm model was designed in [28]. HEVC ME controller design was integrated into ME to realize a coding bandwidth, coding bit rate, and coding-quality-optimized HEVCME design for mobile APSoC, therein utilizing an intelligent power management mechanism. A new Machine Learning based approach was developed in [24] to video Fast Motion Estimation, which improves quality, minimizes power consumption and provides control over the performance. A new block-matching algorithm for fast motion estimation was proposed in [25] called Star Diamond Search with Adaptive Threshold (SDth) was two steps algorithm.

3. Methodology

3.1. Fowlkes-Mallows Correlated Cohen Kappa Coefficient Block Matching based Multi-Layer Perceptron Classifier

Motion is a mixture of transformation as well as variation. Motion is used for evaluation and needs a huge amount of processing. Motion estimation maintains motion among two or more frames. Motion compensation employs motion data for rebuilding the video. ME minimizes temporal redundancy through consecutive frame matching in video analysis applications. Every block is evaluated using candidate blocks for achieving motion. ME evaluates the movement of objects within the imaging system for attaining the vectors denoting estimated motion. Motion compensation employs for attaining data compression. ME eliminates temporal redundancy of better correlation among the consecutive frames.

Block matching determines motion and creates the motion vector. Block matching is used for hardware realization due to consistency. From block matching, each frame is separated within blocks.

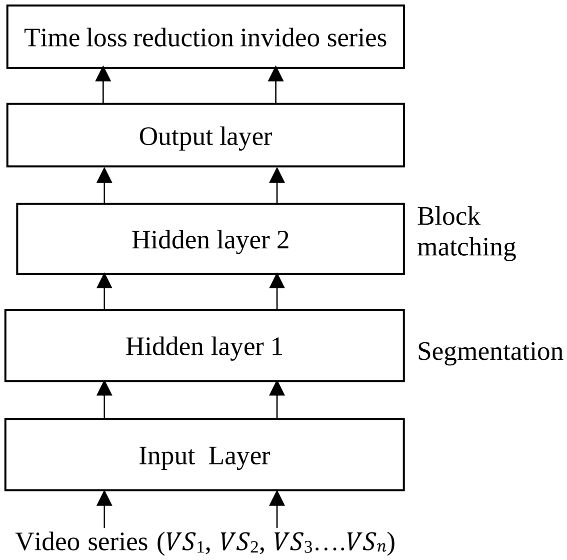

Fig. 1 Structure diagram of deep multi-layer perceptron

Every block comprises the luminance and chrominance blocks. ME is carried out on a luminance block. Every luminance block is matched against candidate blocks within the search area. The best candidate block is identified, as well as movement is verified. Many research works are carried out on developing efficient block-matching. However, the power and time consumption was not minimized. To solve this problem, Fowlkes–Mallows Correlated Cohen Kappa Coefficient Block Matching-based Multi-Layer Perceptron Classifier (FMCCKCBM-MLPC) Model is introduced. The key aim of the FMCCKCBM-MLPC model is to perform motion estimation with minimum time loss in video series. Multi-Layer Perceptron (MLP) is used for performing the classification with multiple layers.

Figure 1 explains the recursive deep neural network diagram in the FMCCKCBM-MLPC model to minimize the time loss in video series. The input layer gathers the number of video series '$VS = VS_1, VS_2, \dots, VS_n$'. The input is transmitted to the hidden layer 1. In hidden layer 1, the segmentation is carried out to minimize the time loss. In hidden layer 2, the block matching is carried out with the segmented blocks. The neuron activity at the input layer is devised as,

$$Inp(t) = \sum_{k=1}^{n} VS_k * weight_i + Bias \quad (1)$$

From (1), 'VS_k' symbolizes the number of input video series. '$weight_i$' denotes the initial weight. 'B' denotes the bias value '+1'. The input is sent to the first hidden layer. Segmentation is performed with Regularized Principal Component Regression. Regularized Principal Component Regressive Segmentation process is carried out in the FMCCKCBM-MLPC model at the hidden layer 1 to divide the video series into the number of blocks through determining the pixel of the video series.

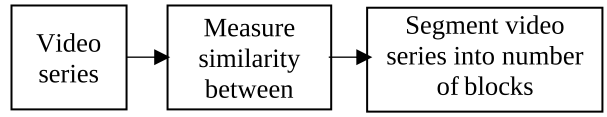

Fig. 2 Regularized principal component regressive segmentation

Regularized Principal Component Regressive Segmentation is a statistical method determining the linear relationship between their pixels in video series. Regularized Principal Component Regressive Segmentation is employed for determining the unknown regression coefficients. The explanatory variable is employed as a regressor. Regularized Principal Component Regressive Segmentation handled the situations with the low-variance principal components in the regression step.

Figure 2 illustrates the video segmentation process using Fowlkes–Mallows Indexed Principal Component Regression algorithm in the FMCCKCBM-MLPC model. The regression function considered the input video with extracted pixels. The regression functions to examine the pixel of the input images through Fowlkes–Mallows Correlated Index. Fowlkes–Mallows Correlated Index is employed to find the linear relationship between the pixels in the video series. It is formulated as,

$$FMCI = \sqrt{\frac{p_i}{p_i+p_j} \cdot \frac{p_j}{p_i+p_j}} \quad (2)$$

From (2), '$FMCI$' denotes the Fowlkes–Mallow's correlated coefficient. 'p_i' denotes the pixel of the video, 'p_j' denotes the neighbouring pixel of the video. The coefficient provides the similarity value range between 0 and 1 ($0 \leq FMCI \leq 1$). Based on the similarity value, the pixels are partitioned into a number of blocks.

3.2. Cohen's Kappa Coefficient based Block Matching

After the segmentation process, block matching is performed in FMCCKCBM-MLPC Model through cohen's kappa coefficient in the hidden layer 2. The relevant pixel is considered as an input of the next hidden layer. The output is classified into two different classes. FMCCKCBM-MLPC Model uses the input as selected relevant pixels '$P = p_1, p_2, \dots, p_m$' and number of classes '$C = c_1 \; and \; c_2$'. Cohen's kappa coefficient determines the agreement between two relevant pixels classified into N categories. It is calculated as given below,

$$\kappa = 1 - \frac{1-p_i}{p_t} \quad (3)$$

From (3), 'κ' denotes the cohen kappa coefficient results. 'p_i' denotes the mean square of the difference between pixels. 'p_t' symbolizes the testing pixel value. The output of the coefficient returns the value between 0 and 1.

Table 1. Pseudo-code of the FMCCKCBM-MLPC model

// **Algorithm 1: Fowlkes–Mallows Correlated Cohen Kappa Coefficient Block Matching based Multi-Layer Percepton Classifier**
Input: Video series '$VS = VS_1, VS_2, \dots, VS_n$',Output class '$C = C_1, C_2$' **Output**: Minimizes the time loss in the video series
Begin 1. Collect the number of video series $VS = VS_1, VS_2, \dots, VS_n$ into an input layer 2. Transform the video series into the firsthidden layer 3. For each video series 4. Measure Fowlkes–Mallows correlation index ---hidden layer 1 5. If ($FMCI$ = +1) then 6. Pixels are adjacent 7. else 8. Pixels are not adjacent 9. Perform pixel-based segmentation process 10. End if 11. For each

As a result, the hidden layer output is attained as,

$$Hidden(t) = [\sum_{k=1}^{n} VS_k * weight_i] + [weight_{ih} * Hidden(t-1) \quad (4)$$

From (4), '$\mathrm{Hidden(t)}$' symbolizes the hidden layer output. '$\mathrm{Hidden(t-1)}$' denotes the output from the previously hidden layer. '$\mathrm{weight_{ih}}$' indicates the weight between the hidden layer and the input layer. Classification is attained at an output layer. It is formulated as,

$$Output(t) = [weight_{oh} * Hidden(t)] \quad (5)$$

From (5), '$\mathrm{Output(t)}$' symbolizes the output of a deep multi-layer neural network. '$\mathrm{weight_{oh}}$' symbolizes the similar weight between the hidden layer and the output layer. By this manner, the repeated blocks are exactly predicted with higher accuracy depending on the correlation coefficient. The pseudo-code of the FMCCKCBM-MLPC Model is explained in Table 1.

Algorithm 1 explains the video loss reduction through Multi-Layer Percepton Classifier in FMCCKCBM-MLPC Model. The number of video series is gathered from the input dataset. After that, the segmentation process is performed in hidden layer 1 to reduce the time and space complexity. After that, block matching is carried out using the cohen kappa coefficient. Based on the correlation measure, the repeated blocks are predicted in hidden layer 2 to minimize the time loss. In this way, the block matching performance gets improved in VLSI architecture.

4. Software used and Result Analysis

Simulation of FMCCKCBM-MLPC Model is executed using Xilinx ISE design tool for performing the motion estimation in the VLSI architecture. Xilinx ISE is the development tool implemented by the Xilinx software. Xilinx ISE is the software tool from Xilinx to combine and detect design tools. ISE planned the embedded firmware for the integrated circuit (IC) product family. ISE constructed the design with an RTL diagram to replicate the project reaction the programming language used in the VERILOG. Optimizing the transistor size is essential to minimize delay without power consumption. Device utilization of both existing and proposed methods is demonstrated in Tables 2, 3 and 4.

Table 2 and 3 illustrates the device utilization of Quadrant-based search with OME. The feature structure includes the number of multipliers with slice registers and LUTs. The control element identified the estimation to handle the functional assessment. The adaptive controller employed the high granularity local power gating. Motion estimation attained energy saving varying from 9% to 25% with a delay overhead of 6% reduced to 4% through improving the area overhead from 3% to 15%. Table 4 demonstrates the device utilization of the proposed FMCCKCBM-MLPC Model. From Table 4, the proposed FMCCKCBM-MLPC Model comprises the 1,26,800 slice registers, 63,400 slice LUTs, 15,850 occupied slices, and slices with related and unrelated logics number of bonded IOB. Table 5 illustrates the simulation results of existing and proposed motion estimation methods. The area is described as the combination of cells in the VLSI structure. Power is defined as the amount of dynamic, internal, net and leakage power. Delay is essential in motion estimation. Speed is the rate at which VLSI architecture gets constructed with an adder enhancement.

Table 5 provides area, delay, PSNR, and power with two existing FMCCKCBM-MLPC techniques. FMCCKCBM-MLPC Model attains better results with different metrics. The below figure explains the graphical estimation of four parameters of motion estimation methods in VLSI architecture. Figures 3, 4, 5 and 6 illustrate the performance analysis of the area, delay, power and PSNR to various motion estimation techniques. The area of the proposed FMCCKCBM-MLPC Model is reduced by 22% and 21% compared to the quadrant-based search algorithm and block-based motion estimation technique, respectively. The delay of the proposed FMCCKCBM-MLPC Model is reduced by 40% and 26% than [1] and [2], respectively. The power consumption of the proposed FMCCKCBM-MLPC Model is reduced by 23% and 19% than the quadrant-based search algorithm and block-based motion estimation technique, respectively. The PSNR of the proposed FMCCKCBM-MLPC Model is increased by 10% and 4% than [1] and [2], respectively.

Table 2. Device utilization of existing quadrant-based search algorithm

Device Utilization Summary			
Logic Utilization	**Used**	**Available**	**Utilization**
Number of SliceLUTs	178	63400	0%
Number of fully used LUT-FF pairs	0	178	0%
Number of bonded IOBS	71	210	33%
Number of BUFG/BUFGCTRLs	1	32	3%

Table 3. Device utilization of existing motion vector with optimization motion estimation (OME)

Device Utilization Summary (Estimated values)			
Logic Utilization	**Used**	**Available**	**Utilization**
Number of SliceRegisters	604	93120	0%
Number of Slice LUTs	904	46560	1%
Number of fully used LUT-FF pairs	280	1228	22%
Number of bonded IOBS	16	240	6%
Number of Block/FIFO	1	156	0%
Number of BUFG/BUFGCTRLs	3	32	9%

Table 4. Device utilization of the proposed FMCCKCBM-MLPC model

Device Utilization Summary (Estimated values)			
Logic Utilization	**Used**	**Available**	**Utilization**
Number of SliceRegisters	3	12,776	1%
Number used asFlip Flops	0		
Number usedLatches	0		
Number usedLatch-thrus	0		
Number used asAND/OR logics	0		
Number of sliceLUTs	166	63,400	1%
Number of used aslogic	166	63,400	1%
Number using 06output only	153		
Number using 05	0	372	6%
output only			
Number using 05 and 06	13		0%
Number of occupied slices	80	15.850	1%
Number with an unused Flip Flops	163	166	98%
Number with an unused LUT	0	166	0%

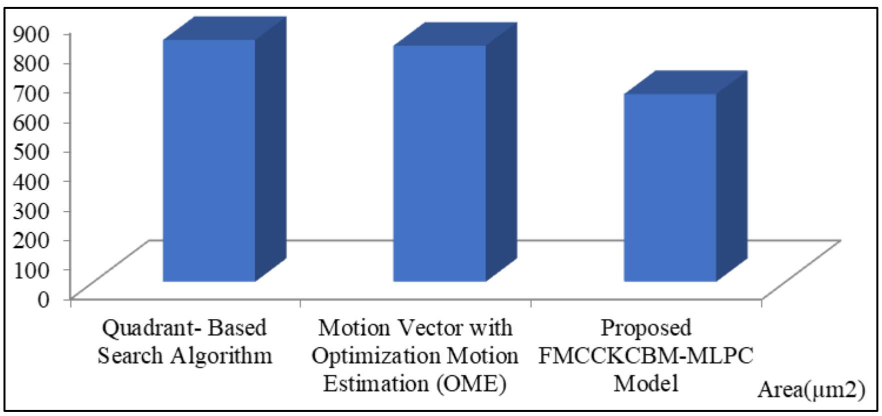

Fig. 3 Measurement of area

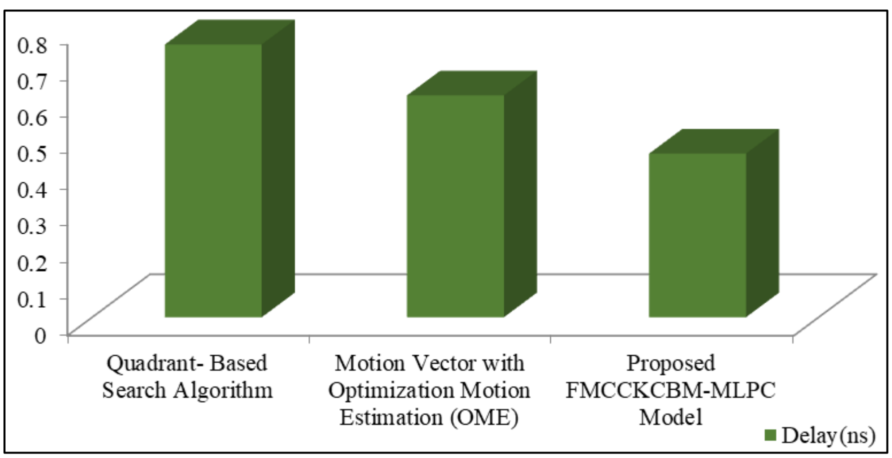

Fig. 4 Measurement of delay

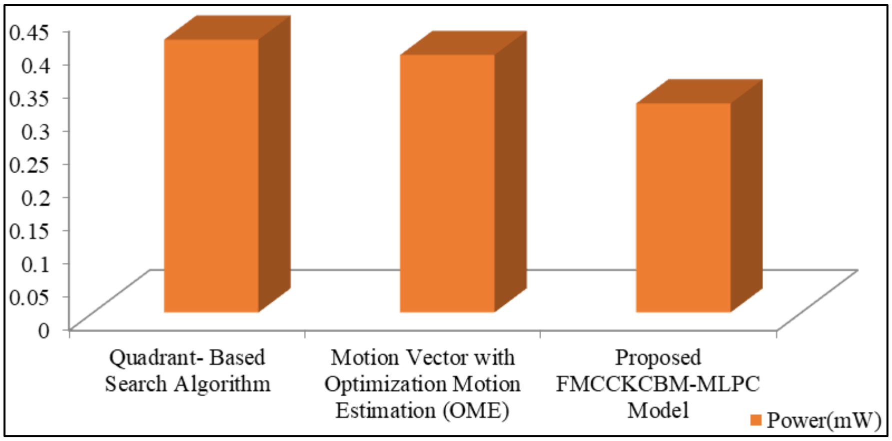

Fig. 5 Measurement of power

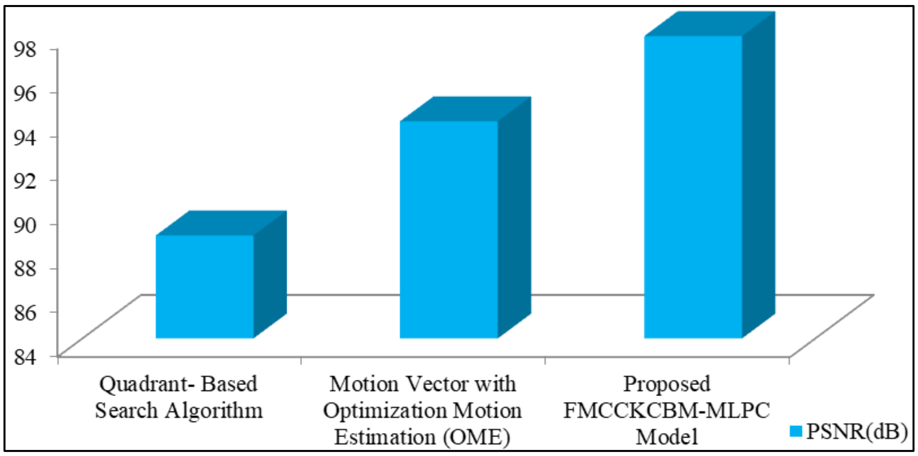

Fig. 6 Measurement of PSNR

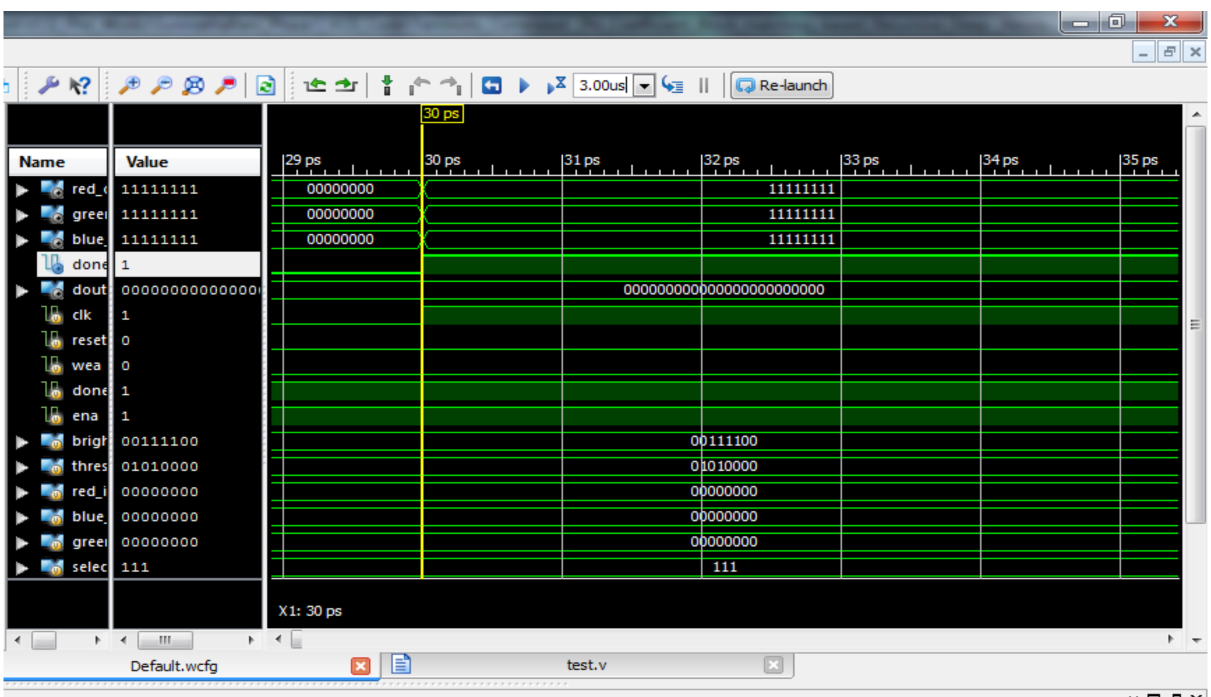

Fig. 7 Simulation results of proposed FMCCKCBM-MLPC model

Table 5. Tabulation of existing and proposed motion estimationmethod in terms of area, delay and power

Techniques	Motion estimation	Area (μm^2)	Delay (ns)	Power (mW)	PSNR (dB)
Motion estimation method	Quadrant based search algorithm	818.35	0.75	0.410	88.68
	Motion vector with optimization motion stimation	799.11	0.61	0.387	93.87
	Proposed FMCCKCBM-MLPC model	635.25	0.45	0.314	97.75

Figure 7 describes the simulation results of the FMCCKCBM-MLPC Model. From the figure representation, two inputs are taken for efficient motion estimation in FMCCKCBM-MLPC Model. The key objective of the FMCCKCBM-MLPC Model is to enhance ME. A block-matching algorithm is used to attain an efficient search algorithm. The designed FMCCKCBM-MLPC Model performed the Hybrid Adaptive road sample search. Adder uses a transmission rate and a multiplexer to eliminate the interconnection difficulties and achieve enhanced impacts.

5. Conclusion

The effectiveness of the proposed FMCCKCBM-MLPC Model gets enhanced for performing the motion estimation in VLSI design. The objective of the FMCCKCBM-MLPC Model is to enhance the motion estimation of video series. Multi-Layer Perceptron examines the feature for performing classification with multiple layers. The segmentation process is performed through Fowlkes–Mallows Regularized Principal Component Regression to minimize the time loss. Cohen Kappa Coefficient performed block matching with the segmented blocks. This way, the performance of motion estimation improves in the VLSI architecture. FMCCKCBM-MLPC Model is rapid and exact, whereas VLSI hardware implementation is a minimal delay. The hardware complexity of the proposed FMCCKCBM-MLPC Model gets reduced by 35% to 39% when designed with block estimation methods.

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