Implementation of a modified K-NN Algorithm based 256-QAM using FPGA

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Abstract

This paper proposes the design of K-NN algorithm based 256-Quadrature Amplitude Modulation for the fault identification. The main purpose of the proposed method is to use the quadrature amplitude variables of signals in which QAM is used to achieve high levels of spectrum efficiency. Generally, the KNN algorithm is used for both classification as well as regression predictive problems. Though there are several Machine Learning algorithms to classify, the KNN algorithm is an effective way to identify the fault based on the Euclidean distance between variables. The QAM is a modulation technique that combines the phase and amplitude modulation of a carrier wave into a single channel. The QAM may occur with error with respect to the amplitude or phase when fused with Sine and cosine waves. The proposed design utilizes the resolution of 8 bits to analyze 256 unique combinations of signals. The HDL code is developed for the proposed method and real time validated using the FPGA device. The performance characteristics such as power , area and timing are verified using the Xilinx Tool.

Keywords: *Quadrature amplitude modulation, Modified KNN algorithm, Field Programmable Gate Array, Fault Analysis.*

I. Introduction

Quadrature amplitude modulation (QAM) is an advanced flexibility technique that is widely used in Wi-Fi communication systems. It combines phase and amplitude modification. QAM offers some important advantages in data communication. QAM techniques are utilized in communication engineering due to its high data rate and easy way of representing signal in binary form. The higher resolution of QAMs are used in digital video processing, data transmissions, optical communication system.

Recently, many works have focused on the use of machine learning technology and algorithms based technological development. The use of Machine Learning and Deep Learning in fault analysis of real time applications plays a pivotal role in the performance evaluation of the circuits. The KNN algorithm based on m-QAM demodulator has been addressed in parallel execution of the signals used in the design [1]. The design and implementation of a KNN hardware accelerator is targeted at modern System-on-Chips. The QAM platform employs a user-based sorting device dedicated to KNN, which is more efficient and has a lower energy footprint than traditional sorters [2].

The spatial subdivision method is applied in unevenly distributed point clouds to accomplish efficient localization and mapping in smart vehicles [3]. Considering the constraints associated with mobile devices, there is efficient hardware architecture to accelerate the K-nearest neighbor classifier and this architecture is evaluated in terms of speed, space, and accuracy [4]. The ML algorithm is to use ultra-high frequency passive radio frequency identification technology to provide indoor real-time location tracking. Regression models are utilized to create a fingerprint database based on statistically valid regression models and evaluated by different factors, namely movement features and performance [5]. The KNN computer hardware acceleration of 65nm CMOS that combines digital computer hardware with a memory device designed for deep neural networks and SRAM enables advanced filtering [6].

The use of Hardware Performance Counters as malware detectors is gaining traction. In high-performance computing, special purpose registers are used to track low-level micro-architectural events, such as branching and cache hits. To estimate the effectiveness of classifying malware, HPC values are obtained during execution [7]. The K-Nearest Neighbor classifier is used to detect duplicate news on social media. There is a feature of detecting duplicated news on social media that makes detecting method inefficient. The accuracy of this model is 79% [8]. The concept of using an antenna's radiation pattern in fingerprinting is explored. The focus was on determining the distance between an RFID reader and a tag. Regression and classification models of the RAC-KNN were used for this purpose [9].

Using the FPGA, a rate-adaptable (RA) Prefix-free Code Distribution Matching (PCDM) encoder is been proposed. PCS technology operates at a lower cost than other models and enables high-through put optical communications to satisfy channel capacity [10]. The system consists of an inexpensive 2-bit programmable coding meta surface operating at around 3.2 GHz and an efficient optimization algorithm for generating high-order OAM-carrying beams in a reprogrammable fashion. In this way, the QAM can generate topological charges and vortex centers controlled by electronic means [11].

The paper is organized as follows: 1, Introduction with Literature survey is discussed in this section. 2. The proposed KNN algorithm based QAM is presented. Section 3 shows the results and discussion about the fault identification and analysis of the proposed method. Finally, concluding the paper in section 4 followed by references.

II. The proposed KNN based 256 Quadrature Amplitude Modulation

In the proposed project, the modified KNN algorithm is used to identify the errors in the generated 256 QAM signals. In general, the Quadrature amplitude involves in the fusion of two signals into single for the purpose of communication through the channel. The QAM consists of a combination of amplitude shift keying and phase shift keying which changes both the amplitude and phase based on the values defined for the 8 bits. The block diagram of the QAM for the resolution of 8 bits is given in Fig.1. The 8 bits value is split into two halves as 4 bits for Q (Higher order 4 bits) represented as Q2, Q1, Q0 and Q' and 4 bits for I (Lower order 4 bits) represented as I2, I1, I0 and I'. The "Q" signifies the SINE wave and "I" signifies the COSINE wave with the first 3 bits say Q2Q1Q0 and I2I1I0 indicating the magnitudes of the different amplitude levels. The fourth bit of the Q' and I' depicts the phase shift of 180 degree for the value of '0' and no phase shift for the value of '1'. Table 1 presents the possible combination of values SINE and COSINE with the amplitude levels and phase for the given value. The 4 bits in SINE and COSINE can generate 16 possible combinations of bits. The resolution of 8 bits would generate 256 unique combinations for the QAM.

Fig 1. Block Diagram of the proposed KNN based 256-QAM

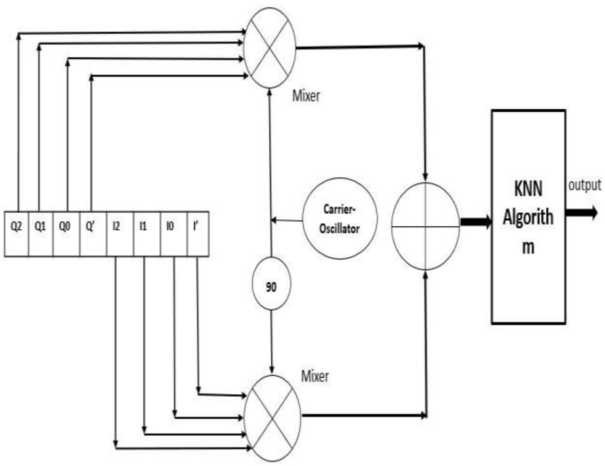
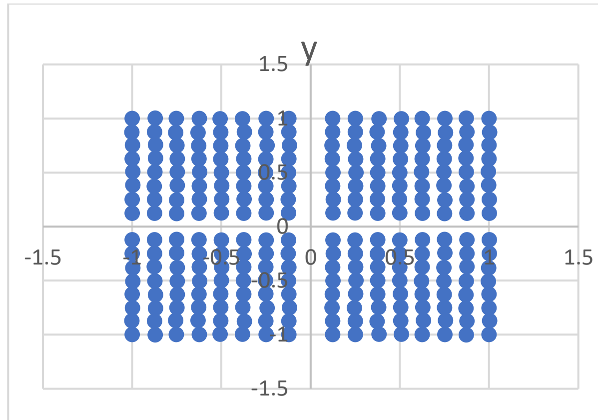


Table 1: Two waves at eight different voltage levels

Sine wave				Voltage	Cosine wave			
Q_2	Q_1	Q_0	Q^1	levels	I_2	I_1	I_0	I^1
0	0	0	0	0.125	0	0	0	0
0	0	0	1		0	0	0	1
0	0	1	0	0.250	0	0	1	0
0	0	1	1		0	0	1	1
0	1	0	0	0.375	0	1	0	0
0	1	0	1		0	1	0	1
0	1	1	0	0.5	0	1	1	0
0	1	1	1		0	1	1	1
1	0	0	0	0.625	1	0	0	0
1	0	0	1		1	0	0	1
1	0	1	0	0.750	1	0	1	0
1	0	1	1		1	0	1	1
1	1	0	0	0.875	1	1	0	0
1	1	0	1		1	1	0	1
1	1	1	0	1	1	1	1	0
1	1	1	1		1	1	1	1

The generated 256 values of the QAM are utilized to plot the constellation diagram that gives a graphical representation of signal components in digital modulation. This plot presents the graph of scattering dots indicating the signal amplitude and angle for the QAM. The shift in phase in the modulating signal from the modulated signal is given in the anti-clockwise direction in the horizontal plane. The amplitude is considered as the space between the point and the origin. The constellation diagram for the 256 QAM is shown in figure 2.

Fig 2: Constellation diagram for the proposed KNN based QAM

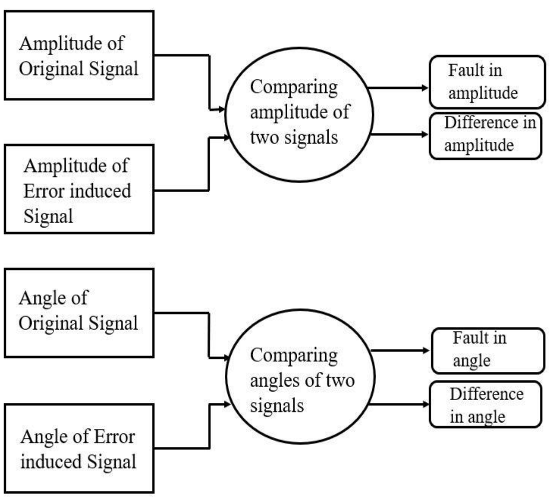


From the constellation diagram of the 256 QAM, the amplitude and angles can hold onto some error during its operation. This error occurrence happens with the evaluation of amplitude and angles of the 256 QAM values. The proposed method includes the identification of these errors using the K-Nearest Neighbor (KNN) algorithm. In this work , the KNN algorithm is used to check the fault occurrence in the QAM values. The KNN algorithm is one of the machine learning algorithms used for classification. The KNN is suitable for the supervised learning and has deep application in pattern recognition, data mining and access acquisition.

In this proposed work, modified KNN helps to find the errors at the output stage of the modulator that generates 256 QAM signals. This algorithm will reduce the number of comparisons and result in an accurate output. For the sake of validation of the developed KNN algorithm, the errors are induced in the QAM and checked for the nearest distance between the 256 values of QAM. The iteration of K is fixed at 3, to identify the error in the QAM by choosing the majority of the 3 outcomes. The modified KNN algorithm checks for error in the amplitudes and angles of the 256 QAM as depicted in figure. 3. For calculating the distance between the error and original samples, the Euclidean formula is utilized.

The HDL code is developed for the modified KNN algorithm by making use of the peak digitized amplitude values. For this both the amplitude and angle should be taken as inputs for all the 256 signals and a new wave with induced errors need to be considered to check the fault. Using developed HDL based KNN code checks if both the signals are having same values of angle and amplitude, else the fault will be determined. And if there is any fault, the algorithm initiates to check the difference of the two waves and there is no need of comparing the signals with other angles directly algorithm will check for the fault at particular position or at specific angles.

Fig 3: Application of modified KNN Algorithm implemented in QAM



III. Results and Discussions

The proposed KNN based fault detection in 256 QAM is developed using the HDL code. The simulation output for the proposed method consists of the following variables as declared in the code.

- a: angle of original signal
- a1: angle of error induced signal
- da: difference between the angles of original and error induced signal
- fa: fault between the angles of original and error induced signal
- m: amplitude of original signal
- m1: amplitude of error induced signal
- dm: difference between the amplitudes of original and error induced signal
- fm: fault between the amplitudes of original and error induced signal
- clk: Clock

The original signal amplitude and angels are used to check the fault in that signal. The modified KNN is used to check the amplitudes m and m1 of two different signals at the same angle. Then while checking this with the original signal and error induced signal if there is any difference it will show the fault as 1 otherwise it will show the difference and fault as 1.

In simple way, in this simulation output a and m are the amplitude and angle of the original signal and a1 and m1 are the amplitude and angle of the error induced signal. When both the amplitudes a and a1 are compared using modified KNN algorithm the fault can be seen in fa and fm in the form of 0 or 1 similarly with the angles m and m1. If the fault is equal to 1 then it will find the difference between respective positions which represents in the form of da and dm. Or else if the fault is 0 then the difference will be 0 by default. This will be done for all 256 combinations for both the amplitude and angle. And all this will be in integer format. For whole process we need to give the clock (clk) and check the output. The simulation output of the porposed method is given in figure.4

Fig.4 Simulation output of the proposed KNN based QAM using the MODEL SIM Tool

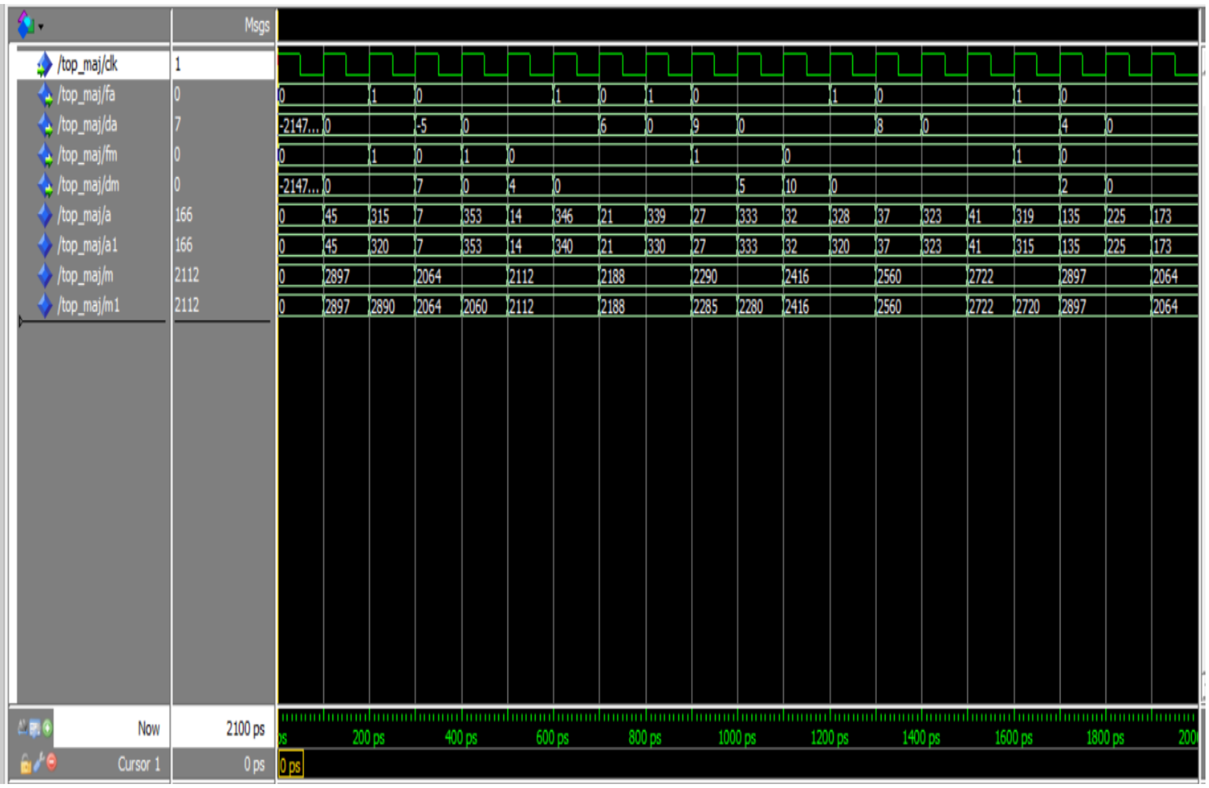


Fig.5 RTL Schematic of the proposed KNN based QAM using the Xilinx Tool

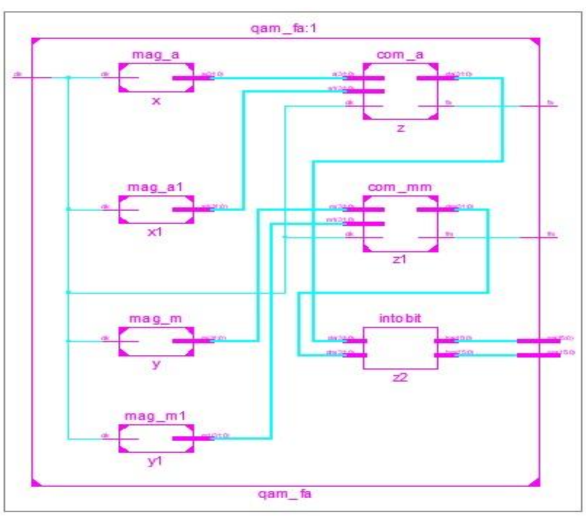


Figure 5 indicates the RTL schematic for the proposed method that outlines the code were the input nodes output nodes and the connections between the simple codes in the top module. Above Schematic shows the connections of operations which are carried out in whole HDL program. mag_a and mag_a1 are the amplitudes of original and error induced signals where as mag_m and mag_m1 are the angles of original and error induced signals. And com_a is comparing angles of two different signals, com_mm is comparing the phase of two signals. Then there are converted to integer form.The dynamic power of the user design as a result of the input data pattern and the design internal activity is referred to as dynamic power. This instantaneous power fluctuates with each clock cycle and is determined by the voltage levels.

Fig.6 Power Analysis the proposed KNN based QAM using the Xilinx Power Analyser

Device	
Family	Spartan6
Part	xc6slx9
Package	csg324
Temp Grade	C-Grade
Process	Typical
Speed Grade	-3
Environment	
Ambient Temp (C)	25.0
Use custom TJA?	No
Custom TJA (C/W)	NA
Airflow (LFM)	0
Heat Sink	None
Custom TSA (C/W)	NA
Characterization	
Production	v1.3,2011-05-04

On-Chip	Power (W)	Used	Available	Utilization (%)
Clocks	0.001	1	---	---
Logic	0.000	73	5720	1
Signals	0.000	120	---	---
BRAMs	0.000	*	*	*
IOs	0.008	35	200	18
Leakage	0.015			
Total	0.024			

Thermal Properties	Effective TJA (C/W)	Max Ambient (C)	Junction Temp (C)
	30.5	84.3	25.7

Supply Summary Source	Voltage	Total Current (A)	Dynamic Current (A)	Quiescent Current (A)
Vccint	1.200	0.005	0.001	0.004
Vccaux	2.500	0.003	0.000	0.003
Vcco33	3.300	0.003	0.002	0.001

	Total	Dynamic	Quiescent
Supply Power (W)	0.024	0.009	0.015

The Power Analysis is up to date.

The total current, Dynamic current and Quiescent are represented in Ampere (A). Total current is 0.003A where as dynamic current is 0.001 A on average and the Quiescent current is 0.003 A on average as shown in figure 6. Effective device utilization can improve operations, support procurement decisions, and aid in capital expenditure management. Companies that have access to device utilization data can compare and contrast device utilization across different facilities in order to identify and improve operational efficiency of underutilized equipment. Device utilization is a valuable tool for answering both short and long-term troubleshooting and planning questions. And the below table shows the availability and usage of different components or logics for the code simulation. The registers, flipflops, LUTs, and other main logic utilization is been represented in the table,

Table 2: Device Utilization Summary for the proposed KNN based QAM

Device Utilization Summary			
Slice Logic Utilization	**Used**	**Available**	**Utilization**
Number of Slice Registers	33	11,440	1%
Number of Slice LUTs	73	5,720	1%
Number used as logic	72	5,720	1%
Number of occupied Slices	22	1,430	1%
Number of MUXCYs used	44	2,860	1%
Number with an unused Flip Flop	40	73	54%
Number of fully used LUT-FF pairs	33	73	45%
Number of slice register sites lost to control set restrictions	7	11,440	1%
Number of bonded IOBs	35	200	17%
Number of LOCed IOBs	35	35	100%
Number of RAMB8BWERs	4	64	6%
Number of BUFG/BUFGMUXs	1	16	6%
Average Fanout of Non-Clock Nets	2.31		

IV. Conclusion

In this paper, the modified KNN algorithm for 256 Quadrature amplitude modulation is successfully implemented using the FPGA device. This work brings the advantage of avoiding comparisons and allows finding the errors in peak value & phase of the signals. Moreover, these obtained values can be digitized to reduce the complexity of the coding. Here modified KNN algorithm involves finding errors in the signal's amplitude and angle. Thus the amount of error can be determined and minimized. In future design, a Machine learning algorithm based error correction in higher resolution of QAM could be developed for video processing.

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