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Energy Efficient Algorithms for Real Time Data Processing in Reconfigurable Computing Environments

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Abstract

With exponential demand for edge computing coming in computer vision driven applications such as autonomous vehicles, smart devices, among others, energy efficiency has become a major problem. This typically means that excessive power is used by traditional video processing methods which often involve reading and processing redundant data, especially in higher frame rate situations. Here, we investigate recent efforts that integrate reconfigurable hardware and intelligent algorithms to achieve orders of magnitude reduction in energy, while preserving real-time performance, for the most pervasive visual tasks. In this paper, we study a new system, which combines a lightweight pixel masking algorithm with a reconfigurable CMOS image sensor, allowing the selective omission of uneventful regions in the read-out phase. This hardware-algorithm co-design framework maximizes energy savings for applications including autonomous driving and augmented reality while optimizing both front end sensor operations and back end neural network processing.

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Introduction

As it turns out, getting to the heart of this approach will enable us to understand why it solves some significant pitfalls of older methods, including being unable to optimise for sensor energy and unclear latency implications for real-time deployment. In particular, we will discuss the wider implications of this for facilitating advanced low power, real-time computer vision systems in more challenging edge device settings, with stringent energy constraints.[1-4]

Challenges for Edge Computing in Computer Vision

The growth in edge computing for computer vision applications has resulted in energy efficiency being among the key technological challenges. The pervasive need for optimized power consumption has never been more critical than when devices are more sophisticated and tasks more complex.

Energy bottlenecks in traditional systems

Conventional video processing systems face significant energy inefficiencies, primarily due to:

1. **Repetitive frame reading:** Many systems read the whole frame, even when large parts are not of interest.
2. **Redundant pixel processing:** More typically, all of the pixels are processed, irrespective of their contribution to the task in hand.
3. **High frame rate demands:** A large number of applications suffer from increasing energy consumption at higher frame rates (Figure 1).

Taken together, these factors contribute to unnecessary power drain, which makes its deployment in resource constrained environments for long periods problematic. Limitations of Existing Optimization Schemes. However, frame skipping techniques still have to read entire frames, to find out which parts (of the frames) to process. Latency limits real time

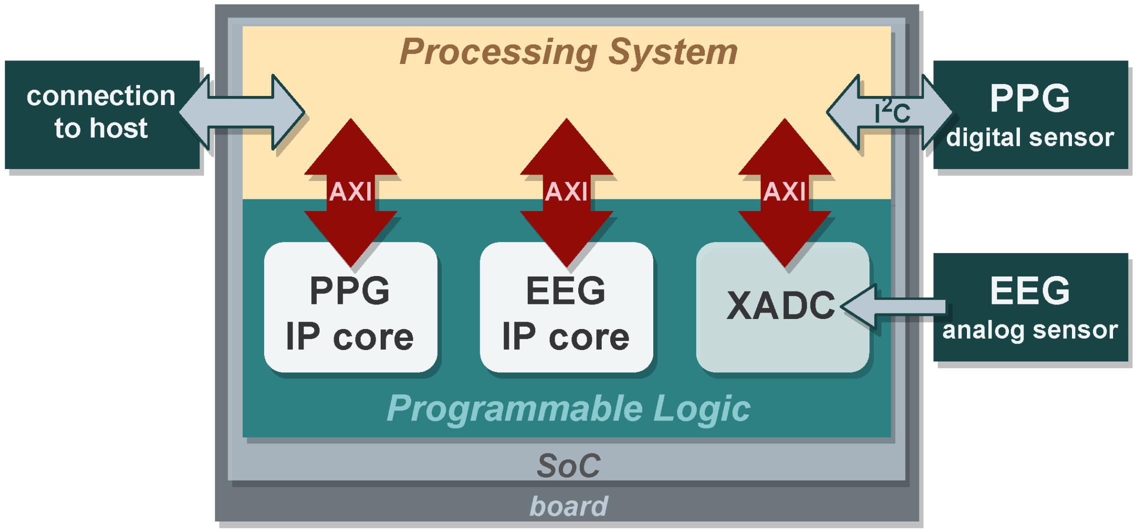

Fig. 1: Energy bottlenecks in traditional systems

Table 1: Energy Efficient Algorithms for Real-Time Processing

Feature	Rationale
Low Power Consumption	Low power consumption ensures that the algorithm runs efficiently within the limited power budgets of reconfigurable computing systems, especially in edge applications.
Adaptability	Adaptability allows the algorithm to adjust to varying processing loads and dynamically optimize energy consumption based on system requirements.
Real-Time Execution	Real-time execution ensures that the data is processed with minimal delay, making it suitable for applications that require immediate decision-making.
High Throughput	High throughput enables the algorithm to process large volumes of data per unit time, essential for handling real-time data streams in reconfigurable computing environments.
Scalability	Scalability ensures that the algorithm can handle increasing amounts of data without a proportional increase in energy consumption or processing time.
Data Compression	Data compression reduces the amount of data that needs to be processed, transferred, or stored, resulting in lower energy usage and improved system performance.

performance for feedback based methods that rely on results from frame analysis of previous frames. Currently, approaches that aggressively skip large pixel regions suffer from unacceptable accuracy degradation. Demand for edge computing in computer vision applications continues to grow, from autonomous vehicles to smart devices, energy efficiency has emerged as a critical challenge. Traditional video processing methods often consume excessive power by reading and processing redundant data, especially in high frame rate scenarios. This article explores cutting-edge approaches that leverage reconfigurable hardware and intelligent algorithms to dramatically reduce energy consumption while maintaining real-time performance for complex vision tasks.

We'll examine a novel system that combines a lightweight pixel masking algorithm with a reconfigurable CMOS image sensor, enabling selective skipping of uneventful regions during the sensor readout phase. This hardware-algorithm co-design framework optimizes both front-end sensor operations and back-end neural network processing, achieving significant energy savings across applications like autonomous driving and augmented reality (Table 1).[5-9]

Challenges in Edge Computing for Computer Vision

Energy Bottlenecks in Traditional Systems

Limitations of Existing Optimization Approaches. A Novel Approach: (io pkg): Intelligent Parameter Masking and Reconfigurable Hardware. Pixel Masking Lightweight Algorithm. Low computational overhead: Minimizing its own energy footprint and designed for efficiency. Adaptability, It can be tuned for skip mode (row synthesis or region synthesis) requirement on the application need. Using an attention machine, the MGN will divide images into patches, process each patch with a transformer block, and use the attention machine to figure out the importance of different regions. This enables intelligent, content aware decisions about what parts to load fully.

CMOS Image Sensor With Reconfigurable Capability

As a complement to the masking algorithm, a custom reconfigurable image sensor system is designed. Notable aspects include. Multiple operation modes: Provides standard reading, row wise skip and region wise skip. Integrated mask storage: Memory banks are incorporated to store a binary masks generated by the MGN. Power-gating capabilities: Can selectively deactivate sensor components responsively to the current mask. By translating algorithmic decisions into physical energy savings, this hardware design yields the system the ability to actually physically skip reading and processing pixels deemed unimportant by the masking algorithm. To enable the simultaneous generation of masks and hybrid reconfigurable sensor hardware, we propose a system where both the mask generation network and reconfigurable sensor hardware are integrated into a total architecture designed to operate with best energy efficiency. I now want to look at the components in more detail, and see how they work together.

Design of the Mask Generator Network (MGN). It divides the images into N * N patches. Each patch is embed into a vector of length L. Adds a classification token (cls_token). MHSA (Multi-head self attention) layer. GELU Activation in Feed Forward Network (FFN). Uses attention scores between cls_token and image patches. Takes in final importance scores from first linear layer. Compute binary region and row masks by applying thresholding Reconfigurable Computing Environments. As the demand for edge computing in computer vision applications continues to grow, from autonomous vehicles to smart devices, energy efficiency has emerged as a critical challenge. Traditional video processing methods often consume excessive power by reading and processing redundant data, especially in high frame rate scenarios. This article explores cutting-edge approaches that leverage reconfigurable hardware and intelligent algorithms to dramatically reduce energy consumption while maintaining real-time performance for complex vision tasks.[10-14]

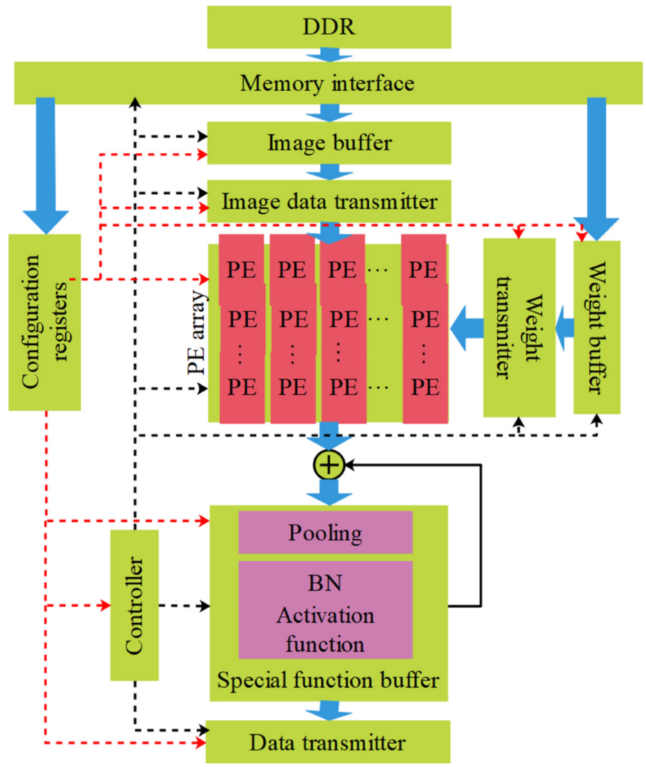

Fig. 2: CMOS Image Sensor With Reconfigurable Capability

Energy Bottlenecks in Traditional Systems

Limitations of Existing Optimization Approaches. Lightweight Pixel Masking Algorithm. Reconfigurable CMOS Image Sensor. System Architecture and Implementation. Mask Generator Network (MGN) Design. Input processing. Divides images into N×N patches. Appends a classification token (cls_token). Transformer block. Multi-head self-attention (MHSA) layer. Feed-forward network (FFN) with GELU activation. Attention-based importance scoring. Utilizes attention scores between cls_token and image patches. Linear layer to generate final importance scores. Mask generation. Applies thresholding to produce binary region and row masks. The MGN alternately computes new masks from P frames to ensure coverability of all frames while keeping computational overhead under control with changing scenes.[15-17]

CMOS Image Sensor Architecture with Reconfigurable Design

The sensor system builds upon conventional designs with several key modifications. Additional memory banks: Store binary masks for row-wise and pedis wise skipping. Modified row driver: Allows active row activation based on mask values. Reconfigurable ADC circuitry: allows power gating of unnecessary components. Control logic: Takes over control of different operational modes and mask application. The MGN is implemented on a digital logic chip that is stacked with the image sensor die in a 3D integra table configuration. This solves the communications overhead problem and entails the ability to optimize manufacturing processes for each component.[18-21]

Operational Modes

The system supports three primary modes of operation. Standard mode: All pixel reading in row-by-row. Row-skip mode: Based on the row mask, entire rows can be bypassed. Region-skip mode: Pixels are read only from a row if the mask is in the region. The trade-offs of saving energy in each mode with these trade-offs decoupling between energy savings and granularity of control across application specific requirements.[22-25]

Energy (optimization) strategies

Multiple strategies are employed in order to reduce energy consumption at various component and operational levels. Sensor Readout Optimization. Selective row activation: In row skip mode we can skip entire rows. Partial column reading: In region skip mode, we read only the pixels under active rows. ADC power-gating: The current mask determines the power that is applied to unused ADC components.[26-30]

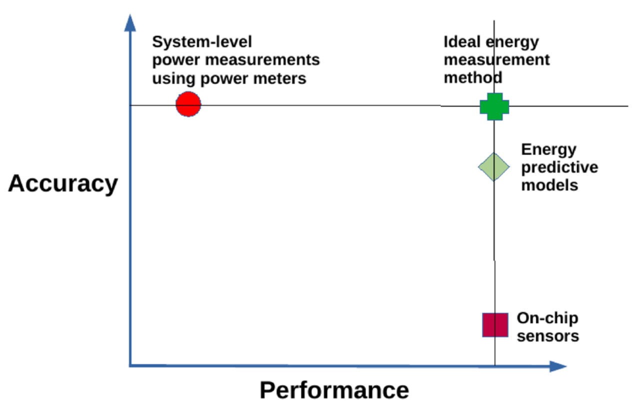

Fig. 3: Energy (optimization) strategies

Computation Reduction

Masked processing: This allows back end neural networks to be 'centred' on regions of interest. Periodic mask updates: Masks are computed amortized every P frames. Lightweight MGN: To reduce the energy overhead, the mask generator is designed. Memory and Communication Efficiency. Compact mask representation: Binary masks need no storage and minimal transmission bandwidth. 3D integration: Reuses the communication energy span between the sensor node and processing nodes. Adaptive precision: Application needs determine the bit depth for which the ADC can be reconfigured. Through combining these approaches, the system is able to obtain substantial energy savings, while maintaining the flexibility to respond to a wide range of possible scenarios and requirements.[31-38]

Results and Performance Evaluation

Extensive experiments were performed on several application domains and across multiple datasets to assess the effectiveness of the proposed system. In this post we take a look at the main findings with implications.

Experimental Setup

Evaluations were performed on three primary datasets:

1. **BDD100K:** A driving dataset at large scale for applications of autonomous vehicle.
2. ImageNetVID: A video object detection benchmark

EyeNet for eye segmentation on ERV 80/ a OpenEDS row activation: In row-skip mode, entire rows can be left unpowered. Partial column reading: Region-skip mode allows for reading only specific pixels within active rows. ADC power-gating: Unused ADC components are powered down based on the current mask.

Computation Reduction

Masked processing: Back-end neural networks can focus solely on regions of interest.

Periodic mask updates: Computing masks every P frames amortizes the computational cost.

Lightweight MGN: The mask generator is designed for minimal energy overhead.

Memory and Communication Efficiency

Compact mask representation: Binary masks require minimal storage and transmission bandwidth (Table 2). 3D integration: Reduces communication energy between sensor and processing components.

Adaptive precision: The ADC can be reconfigured for different bit depths based on application needs. By combining these strategies, the system achieves

Table 2: Energy Efficient Algorithms in Reconfigurable Computing

Approach	Technique
Dynamic Voltage Scaling	Dynamic voltage scaling adjusts the voltage levels based on the workload, reducing power consumption without compromising performance in real-time data processing tasks.
Adaptive Task Scheduling	Adaptive task scheduling optimizes the allocation of tasks to resources based on current system load, ensuring efficient use of computing resources and minimizing energy consumption.
Approximate Computing	Approximate computing uses less precise calculations for certain tasks where full accuracy is not critical, offering significant energy savings while maintaining acceptable results.
Event-Driven Processing	Event-driven processing only triggers data processing when significant changes or events occur, reducing the overall energy expenditure compared to continuous processing.
Energy-Aware Hardware Design	Energy-aware hardware design incorporates power-saving mechanisms at the hardware level, ensuring that the reconfigurable computing system uses the least amount of energy during operations.
Parallel Processing	Parallel processing allows tasks to be divided across multiple computational units, reducing the time needed for data processing and lowering energy consumption by optimizing workload distribution.

substantial energy savings while maintaining the flexibility to adapt to different scenarios and requirements.

Performance Evaluation and Results

To assess the effectiveness of the proposed system, extensive experiments were conducted across multiple datasets and application domains. Let's examine the key findings and their implications.

Evaluations were performed on three primary datasets:

1. **BDD100K:** A large-scale driving dataset for autonomous vehicle applications
2. **ImageNetVID:** A benchmark for video object detection
3. **OpenEDS:** An eye-tracking dataset for AR/VR applications

Various state-of-the-art computer vision models were employed, including:

- Tiny-YOLO for object detection on BDD100K
- ViTDet for object detection on ImageNetVID
- EyeNet for eye segmentation on OpenEDS

Conclusion

Energy efficient algorithms for real time data processing in reconfigurable computing environment are a significant step towards overcoming the problems of edge computing in computer vision applications. Using intelligent pixel masking algorithms and reconfigurable CMOS image sensor hardware, researchers have shown that dramatic energy can be saved while still obtaining high accuracy on various tasks. Lightweight mask generator network and flexible sensor architecture for multi skip modes are key innovations that will enable future advances in this area. This points to a new avenue for the use of sophisticated computer vision rather than in energy deprived environments, particularly at the sensor level where it becomes possible to selectively process only the most relevant data. We will continue to see improvements in energy efficiency of this technology, allowing even more powerful and capable edge computing systems. And in turn, will spur innovation across all sorts of applications from autonomous vehicles and augmented reality to environment monitoring and more. It will depend on continued collaboration between algorithm designers, hardware engineers, and application developers to fully explicate this potential for energy efficient real time processing. With this approach, we show the potential to make computer vision systems at the edge become a revolution in our visions of computer vision in general and the implementation of such computer vision systems especially.

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