Millimeter-Scale Ultra-Low-Power Imaging System for Intelligent Edge Monitoring

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ABSTRACT
Millimeter-scale embedded sensing systems have unique advantages over larger devices as they are able to capture, analyze, store, and transmit data at the source while being unobtrusive and covert. However, area-constrained systems pose several challenges, including a tight energy budget and peak power, limited data storage, costly wireless communication, and physical integration at a miniature scale. This paper proposes a novel $6.7 \times 7 \times 5\text{mm}$ imaging system with deep-learning and image processing capabilities for intelligent edge applications, and is demonstrated in a home-surveillance scenario. The system is implemented by vertically stacking custom ultra-low-power (ULP) ICs and uses techniques such as dynamic behavior-specific power management, hierarchical event detection, and a combination of data compression methods. It demonstrates a new image-correcting neural network that compensates for non-idealities caused by a mm-scale lens and ULP front-end. The system can store 74 frames or offload data wirelessly, consuming 49.6 $\mu\text{W}$ on average for an expected battery lifetime of 7 days.

KEYWORDS
ultra-low-power, tiny-IoT, computer vision, embedded intelligence

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1 INTRODUCTION
Miniaturized Internet-of-Things (IoT) systems have unique advantages over larger devices due to their ability to provide contextual information at the data source. They can be particularly advantageous in healthcare scenarios, where medically implanted devices need to be non-obtrusive for long-term in vivo monitoring [17], and in environmental and animal monitoring applications, where larger instrumentation could disturb the target species or be unable to capture hyper-local data [5][10].

Embedded vision systems have the potential to transform application spaces, such as industrial monitoring particularly in remote or hazardous locations. In spite of these benefits, size-constrained sensing systems pose several fundamental challenges, all of which are exacerbated by using a data-intensive and power-hungry visual sensing modality. The following technical challenges unique to mm-scale systems are tackled in our proposed system:

1) Millimeter (mm)-scale size: Designing a highly area-constrained system requires integrating ultra-low power (ULP) ICs and assembling them to minimize system size. A mm-scale battery is needed to maintain small system dimension, imposing tight energy and peak power constraints.

2) Constrained energy budget and peak current: Millimeter-scale batteries have limited capacities (1-50 mAh) and stringent peak current constraints whereas always-on image sensors have high power consumption, particularly compared to other sensing modalities such as audio. Imaging systems often include computation- and data-intensive digital signal processing and analytic algorithms to perform advanced tasks such as image compression and object/event detection. Deep neural networks (DNNs) can enhance the accuracy of these algorithms but often with the expense of higher number of operations and stored parameters.

3) Limited data storage: Unlike other scalar sensing modalities, raw image data has a significant memory footprint of 3.7Mb per VGA (640×480×3 pixel) frame. A mm-scale system will have a limited amount of on- and off-chip memory available, limiting the storage of image data and the complexity of the algorithms used.

Figure 1: Proposed embedded imaging system
4) Costly wireless communication: ULP wireless communication imposes an overall high energy cost due to low data rates ($\leq$1Mbps), making it inefficient to offload large volumes of data. Commercial off-the-shelf Bluetooth low energy wireless solutions provide a higher data rate but require a reference crystal and matching antenna with relatively high active power consumption of $\approx 10$ mW, placing it outside our system constraints.

5) Non-idealities from mm-scale lens and ULP front-end: Though using a mm-scale lens and ULP imaging front-end enable unobtrusive long-term operation, the resulting images are susceptible to color and geometric distortions. DNN algorithms that have been trained on high quality image datasets suffer significant performance degradation when applied to mm-scale IoT systems.

To address these challenges, work has been done on low-power image sensors [11][22], ULP processors [25][26] and mixed-signal vision ICs [18][30], low-power wireless communication [27][28], efficient neural accelerators [12][20], and optimizing machine learning algorithms for embedded applications [2]. However, limited prior work has combined these approaches into a functional system. Prior demonstrated systems [4][10][13][16][23] either do not incorporate edge intelligence or do not meet the area/power-constraints that motivate this paper.

This paper proposes and demonstrates a fully integrated mm-scale imaging system with deep-learning and image processing capabilities, which is the first of its kind. By using a combination of techniques specific to ULP tiny-IoT systems that tackle the above challenges, we achieve a lifetime of 7 days without recharging the battery and an overall average power consumption of 49.6 $\mu$W. Long-term sustained operation may be achieved by using the system’s energy harvesting IC to recharge the battery.

2 SYSTEM DESCRIPTION

2.1 Stacked custom ICs

The system uses un-packaged and thinned (150$\mu$m) ULP ICs from a family of custom chips that are prior-designed to be vertically stacked and interconnected by attaching wire-bonds between IC bond pads as shown in Fig. 1a. This method increases the number of ICs that can be integrated in the same footprint in comparison to traditional planar 2D chip-to-chip connection on a PCB, allowing the system to achieve a 6.7$\times$7.5mm size and 460mg weight (battery included). The integrated system (Fig. 1 and Fig. 3) consists of:

1) A base-layer: It integrates the following into a single IC die to reduce stacking height and wire bonding complexity.
   - A master controller, containing a Cortex-M0 microprocessor and 16kB SRAM, that is designed for ULP operation, provides the clock and acts as a bus mediator for the open-source ULP bus protocol mBus [24], used for inter-layer communication.
   - A power management unit that generates 0.6V, 1.2V and 3.6V domains from a single battery voltage in the range of 0.9-4V, and maintains high conversion efficiency under loads ranging from nW to hundreds of $\mu$W [14].
   - A radio IC that uses energy-efficient sparse pulse position modulation consuming $<70$ $\mu$W of average active power [6]. It is connected to a metal trace loop antenna integrated within the PCB, and uses a carrier frequency of 1.2GHz and sampling frequency of 240kHz generated by an on-chip oscillator without a crystal reference.

2) A ULP image sensor layer: It supports motion-triggered 12-bit VGA image capture and also near-pixel motion detection on a sub-sampled 32$\times$20 pixel frame at a maximum rate of 170 fps [7].

3) A ULP image signal processing (ISP) layer: It is a revised version of [3], that performs on-the-fly JPEG (de)compression, optical-black pixel calibration, de-Bayering, RGB-to-YUV conversion, and scene change detection when an image is streamed in. It has a H.264 compression engine and 180kB of SRAM to store compressed frames on-chip. A neural engine (NE) with a peak efficiency of 1.5 TOPS/W enables DNN-based frame analysis, and has 426kB SRAM and a custom RISC-like processor. An internal ARM Cortex-M0 microprocessor orchestrates these components. The ISP’s memory banks have separately-controllable power-gating switches to reduce leakage energy for non-retentive data.
4) Two stacked, custom ultra-low-leakage flash layers: They provide a total of 16kB SRAM storage and 256kB flash storage with 11pJ/bit read energy and pW sleep power [8].

5) An energy harvester layer: It is designed to be supplied by a low-voltage source that has a configurable conversion ratio to increase harvesting efficiency for a range of input voltages [15].

6) A solar cell layer: It is for energy harvesting and a global optical communication [21].

7) A 3V 3.4mAh 5.8×1.8mm rechargeable lithium battery: It weighs 130mg with 150μA maximum continuous discharge current and 10μA standard discharge current.

8) A polytetrafluoroethylene (PTFE) tube: It is used as a lens barrel, housing a medical endoscopic lens.

Layers are connected in a daisy-chain configuration and forward mBus transactions between a transmitting and a receiving layers as shown in Fig. 2. The ISP’s image interface connects directly to the image sensor IC pads for raw data and synchronization signals. The ISP’s flash interface allows it to stream (de)compressed image data directly to flash. The power management unit generates power domains that are distributed throughout the system. The battery is recharged by the harvester connected to the solar cell layer.

2.2 System design and integration

The system uses two 4 layer 10×10×0.8mm PCBs. The front of the first PCB is used for wire-bonding the stacked ICs whereas passive components and the solar cell layer are placed on the back (Fig. 1c). The second PCB provides spacing between passive components and the battery so these can be placed above each other.

Since code development and debug on miniature systems is extremely difficult due to limited physical access, we include castellated vias on the outer rims of the system to expose internal signals that connect to compression contacts in our test setup (Fig. 1b). Fig. 3 shows a white outline where the system can be diced a second time into an even smaller form-factor of 6.7×7×5mm (Fig. 1d). With this smaller size, the system loses all exposed probe contacts for debugging and monitoring, thus must be wirelessly programmed through an optical communication interface using the solar cell.

Fig. 1 shows a completed assembly, where the stacked ICs have been encapsulated in black epoxy to block out light due to ULP IC’s light-sensitivity. The solar cell is encapsulated with clear epoxy to be exposed to light. The image sensor is also left exposed by attaching the PTFE lens barrel over it prior to encapsulation.

3 SYSTEM DEMONSTRATION

The system is fully programmable for various applications. As a driving application example, we demonstrate the system for home-surveillance as depicted in Fig. 4. In the demonstrated scenario, the image sensor captures highly sub-sampled (32×20×1 pixel) frames at a rate of 1fps and performs motion detection on-chip. When motion is detected, the ISP receives the sub-sampled frame and performs DNN-based person detection. If a person is not detected, the system returns to continuous motion-detection mode. Otherwise, a VGA frame is taken by the image sensor and streamed to the ISP, which performs image pre-processing, JPEG compression and change detection on the scene by comparing it to a stored reference frame to obtain a pruned (non-rectangular) region of interest (RoI).

Then, the VGA image is corrected for geometric distortion and resized for YOLO-Lite-based face detection. It is a one-shot object detection and localization DNN based on [9], widely researched for embedded vision systems, and we customized it to satisfy the system constraints. If a face is not detected, the system returns to the continuous motion-detection mode. Otherwise, the scene is analyzed by performing DNN-based face recognition. The image RoI is H.264 compressed and stored in the system’s flash layer only when a face is not recognized (i.e., a possible intruder) for optional wireless transmission to a custom gateway. The VGA frame containing an intruder is reconstructed offline.

4 ENERGY MINIMIZATION TECHNIQUES

The chosen mm-scale battery has a limited capacity, making power management crucial to achieve a standalone system with a reasonable operating lifetime. This is particularly challenging for always-on imaging systems, where power consumption is dominated by the continuously running image sensor. Performing DNN-based analysis is costly due to both the computation energy and the megabytes of DNN parameters stored on-/off-chip. However, intelligent DNN-based classifications on the edge is crucial in order to reduce wireless data offloading, which consumes ~15nJ/b and can dominate the system’s energy consumption for large data volumes if not trimmed by DNN-based edge processing.

4.1 Dynamic energy-efficient modes

Most ICs in the proposed system are duty-cycled to optimize the system’s power consumption for the chosen application. Fig. 5 shows
the power breakdown of each mode. For instance, flash ICs are set to sleep during motion monitoring, image capture, and DNN-based scene analysis, consuming only 0.003µW. ISP allows for fine-grained software control of its SRAM banks, which can be in low-power retention mode without loss of data. The NE SRAM is partitioned into 7 variably-sized blocks that can be selectively power-gated to reduce leakage power consumption according to DNN storage requirements. The H.264 engine and image interface memory also have this capability. For example, when the system is in continuous motion-detection mode, the 430kB ISP memory can be power-gated, reducing the leakage power by 1.8×. The power management unit is adjusted at each mode to maximize the efficiency for the dynamic load by modifying current draw, frequency control and up/down conversion ratio, achieving an average efficiency of 64%.

4.2 Hierarchical event detection

A hierarchical event detection (HED) algorithm is employed to prune out irrelevant events that would otherwise wastefully consume energy, particularly when offloading data without determining its value to the user. This approach uses efficient motion detection in the imager front-end and lower complexity DNN-analysis in the ISP back-end to reduce the frequency at which costly VGA images and higher-complexity DNN algorithms are performed, significantly decreasing the system’s average power/energy.

While the image sensor IC is in motion-detection mode, which is performed on the sensor without requiring external processing or storage, other layers are set to sleep so that the system’s power consumption of 48.8µW is dominated by the image sensor. If motion is detected, the system wakes up the ISP, which performs person detection on a sub-sampled frame, consuming 59.6µJ. If a person is detected, the image sensor takes a VGA frame, consuming 349µJ and 14.9µJ to stream the frame into the ISP so that it can perform face detection (643µJ). If a face is identified, face recognition is performed consuming 622µJ. Only when an unregistered face is detected, the frame is stored in flash and offloaded wirelessly.

Fig. 6a shows the average system power for the above scenario, when the image sensor’s motion detection event rate is fixed to once per minute while the person detection (PD) and the un-registered face detection (URFD) event probabilities are varied. The URFD rate combines both face detection and face recognition, and it is assumed that data written to flash and sent wirelessly is uncompressed. This analysis motivates the use of HED for the chosen application, whereas the red top corner demarcates the PD and URFD probabilities where performing HED yields no power savings. In all other scenarios, HED enables significant (up to ≈ 100×) power reduction especially when both URFD and PD rates are low.

Fig. 6b shows the system power breakdown for 3 event cases. When the total event rate is low (‘Case A’), the system power is dominated by the image sensor, while the wireless power dominates as the event rate increases. Notably, the ISP computation power for DNNs is always insignificant compared to the image sensor or radio, showing the benefit of HED in reducing overall power.

5 DATA COMPRESSION TECHNIQUES

The proposed mm-scale imaging system has limited IC area for flash memory and on-chip SRAM, making it critical to employ aggressive data compression techniques for DNN parameters and images.

5.1 DNN parameter compression

High compression of up to 1.5bit/weight is achieved for DNNs by combining weight pruning, non-uniform quantization, Huffman encoding of quantized weights for convolutional layers, and index-based encoding for sparse fully-connected layers. The compressed sizes for person detection, face detection, and face recognition networks are 85kB, 112kB, and 107kB, respectively. Up to 1.75M compressed weights can be stored in the ISP NE on-chip SRAM, which are on-the-fly decompressed when moved to NE local SRAM buffers. Once weights are loaded into the SRAM buffers, they are heavily reused for convolution on large input activations so that the energy overhead of decompressing weights is negligible.

The proposed HED requires multiple DNNs but parameters for less frequently executed DNNs can be stored off-chip in flash to eliminate on-chip SRAM leakage power. This off-chip parameter loading approach, however, increases execution time and incurs energy overhead from inter-chip data movement. We first analyze the event frequency at which this on- vs. off-chip parameter storage trade-off is advantageous for each DNN, and then program each DNN based on the assumption of expected event frequency to minimize the average power consumption.

5.2 Image compression

We use a combination of several compression methods to minimize the data footprint and reduce wireless transmission cost.

5.2.1 JPEG and H.264 compression. The ISP performs on-the-fly JPEG compression on frames streamed in by the image sensor on a macro-block (MCB, 16×16 pixel) level, reducing the memory footprint of storing images on-chip and the SRAM leakage power by 11× and only consuming 14.9µJ. As a result, both a reference and current frame can be stored on-chip in 180kB SRAM rather than off-chip, which otherwise would incur energy overheads of 407µJ/frame. We leverage the ISP’s customized H.264 intra-frame compression engine to reduce the memory footprint of a VGA frame by 23×. We only apply H.264 to the image containing an unregistered face instead of all incoming VGA frames due to the higher latency (than JPEG) that cannot meet the image sensor interface throughput for on-the-fly compression. Though H.264 compression incurs 138% more processing energy than JPEG, at a system-level it reduces the flash write energy from 36.9µJ to 17.4µJ and the wireless egress energy from 37.7µJ to 17.8µJ as it attains a higher compression rate.

5.2.2 Change detection engine. Change detection between a new frame and reference frame stored on-chip can be performed on-the-fly by the ISP. Each MCB of an input frame is encoded into a 64b pattern vector and compared to the stored image vector to create a 40×30 change detection map representing a non-rectangular RoI. We use a customized H.264 algorithm, which removes MCB inter-dependence, to compress only the non-rectangular RoI while unchanged MCBs are pruned. This achieves 135× compression compared to a VGA frame while consuming only 2.8µJ (assuming 86% scene pruning observed in our test dataset). At a system-level, combining change detection and H.264 compression reduces the flash write energy from 17.4µJ to 3.1µJ, the wireless egress energy from 17.8µJ to 3.1µJ, and allows for 74 images to be stored in flash.

5.2.3 Off-system image reconstruction. To reduce the wireless data egress, we reconstruct the current frame offline by only sending the
change detection map (1.2kb) and the H.264 compressed RoI of the current frame (20-30kb) to a custom gateway. We assume that the imager system is deployed in a stationary location, so the system and gateway share the same reference image, which is periodically reprogrammed. A scene is reconstructed by decompressing the unchanged MCBs from the reference image and the changed MCBs from the current frame, reducing the egress data by 130×.

6 IMAGE CORRECTION FOR mm-SCALE LENS AND ULP FRONT-ENDS

Most cameras have ∼60° field of view (FOV), much less than a human. To achieve a larger FOV and capture more information for wide-view scene analysis, our system adopts a wide-angle lens. However, using this lens and a ULP image sensor that lacks sophisticated image pre-processing results in geometric and color distortion, negatively affecting the performance of deep learning perceptual tasks, as was demonstrated when deploying our system.

We propose image-correcting layers (ICL) that can be executed on the ISP NE using supported instructions, such as matrix multiplication and convolution, to compensate for artefacts and distortions (Fig. 7). Since ICL is based on DNN-compatible instructions, it does not require a dedicated hardware accelerator and can be generalized for other constrained systems.

6.1 Distortion modeling and compensation

The fisheye-like lens distortion is modeled by capturing checkerboard images using our system. Geometric distortion correction can be expressed by a mapping between pixels in the distorted image \(I_d\) and the pixels in the correct image \(I_t\):

\[
(x_d, y_d) \rightarrow (x_t, y_t) \quad \forall (x_d, y_d) \in I_d.
\]

Various geometric distortion correction algorithms have been extensively studied and implemented [1][29]. However, for real-time processing, a majority of them require task-specific hardware accelerators which are not available on our system.

Instead, we construct a 640 × 480 × 2 flow field matrix (FFM) that represents vertical and horizontal pixel-displacement vectors based on the offline constructed fisheye distortion model. This ICL can be performed by either the ISP Cortex-M0 or NE by representing the FFM as a sparse fully connected layer. This is advantageous compared to both conventional and learning-based distortion correction methods since it only requires a relatively small correction matrix, which has low memory and computational complexity.

Color correction is performed using a color correction matrix (CCM) that projects the RGB pixel values in the distorted image to the target RGB values at the same location in the corrected image, expressed by a linear equation 

\[
\begin{bmatrix}
R_{ij}^d, G_{ij}^d, B_{ij}^d
\end{bmatrix} = \begin{bmatrix}
R_{ij}, G_{ij}, B_{ij}
\end{bmatrix} A
\]

for pixel \((i, j)\) where \(A\) denotes the CCM. Our CCM is obtained by capturing images of an eSFR (edge spatial frequency response) chart using the proposed system. The color restoration ICL is implicitly accomplished with a linear layer in the custom face detection network. Training data images are modified using the color distortion matrix to emulate the system and implicitly learn the CCM.

6.2 Experiments on ICLs for Face Detection

The proposed ICLs were tested using images in the COCO-faces dataset, a dataset with annotated human faces sourced from COCO 2017 [19], and on images captured by our system. We first pre-train the customized YOLO-Lite network without distortion to speed
up convergence, then apply the distortion models to the training/validation dataset, and include the pre-determined geometric distortion correction ICL. Finally, we fine-tune the YOLO model for color correction.

The performance of our proposed YOLO-Lite face detection network with ICLs is quantified by evaluating the average intersection over union (IoU) and average recall. In Table 1, we evaluate six schemes: 1) original images, 2) images with modeled imager geometric and color distortions, 3) geometric distortion correction, 4) additionally fine-tuning the face detection network using the color distorted training dataset, 5) additionally applying 50% network pruning, 8-bit fixed point quantization, and parameter compression to the final network (necessary for on-chip parameter storage), and 6) testing scheme 5 on a 112×112 pixel gray-scale input image.

The results show a substantial performance drop after applying the modeled distortion to the original image data. Both performance measures are improved to a level close to the original when lens distortion and color restoration ICLs are applied. We experimented on the impact of using a smaller input gray-scale image, together with down-graded intermediate feature maps (case 6 in Table 1). The results demonstrate that our proposed image correction and face detection pipeline give sensible performance in this case, showing that it can be extended to other highly-constrained systems.

### Table 2: Compression gains on overall system operation

| METHOD                | SIZE | PROCESSING ENERGY | FLASH WRITE ENERGY | EGRESS ENERGY | EGRESS TIME | VGA CAPACITY |
|-----------------------|------|-------------------|--------------------|---------------|-------------|--------------|
| Raw VGA Image         | 5.7Mb| 0                 | 407μJ              | 414mJ         | 2 hours     | 0            |
| JPEG                  | 355kb| 11.9μJ            | 36.9μJ             | 37.7mJ        | 11.6 min    | 1            |
| H.264 (QF=20)         | 158.2kb | 28.3μJ           | 17.4μJ             | 17.8mJ        | 5.5 min     | 12           |
| H.264 + CD (QF=20)   | 27.4kb | 14.8μJ           | 3μJ                | 3.1mJ         | 57s         | 74           |

This paper proposes a novel mm-scale, standalone system with deep-learning and image processing for intruder detection, with an average power consumption of 49.6μW and expected lifetime of 7 days without recharging. It achieves a miniature size by vertically stacking ULP custom ICs, and satisfies a tight memory and energy budget through a combination of data/energy management methods. We present image-enhancement layers to improve DNN performance in constrained embedded systems. Comprehensive system-level analysis was conducted to quantify the gain of proposed techniques, which can be generalized to other ULP systems. Having demonstrated a tiny-IoT intelligent imaging system, analysis through a sociotechnical and ethical lens is an essential next step; we invite future work on topics such as security and privacy.

8 CONCLUSION

This paper proposes a novel mm-scale, standalone system with deep-learning and image processing for intruder detection, with an average power consumption of 49.6μW and expected lifetime of 7 days without recharging. It achieves a miniature size by vertically stacking ULP custom ICs, and satisfies a tight memory and energy budget through a combination of data/energy management methods. We present image-enhancement layers to improve DNN performance in constrained embedded systems. Comprehensive system-level analysis was conducted to quantify the gain of proposed techniques, which can be generalized to other ULP systems. Having demonstrated a tiny-IoT intelligent imaging system, analysis through a sociotechnical and ethical lens is an essential next step; we invite future work on topics such as security and privacy.
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