AI-on-skin: Enabling On-body AI Inference for Wearable Artificial Skin Interfaces

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Figure 1: AI compute architectures - (a) Off-body BLE compute (b) On-body centralized microcontroller compute and (C) On-body AI-on-Skin distributed compute architecture

ABSTRACT

Existing artificial skin interfaces suffer from the lack of on-skin compute that can provide fast neural network inference for time-critical application scenarios. In this paper, we propose AI-on-skin - a wearable artificial skin interface integrated with a neural network hardware accelerator that can be reconfigured across diverse neural network models and applications. AI-on-skin is designed to scale to the entire body, comprising tiny, low-power, accelerators distributed across the body. We built a prototype of AI-on-skin that covers the entire forearm (17 by 10 cm) based on off-the-shelf FPGAs. Our electronic skin based prototype can perform (a) handwriting recognition with 96% accuracy, (b) gesture recognition with 95% accuracy and (c) handwritten word recognition with 93.5% accuracy.

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AI-On-Skin achieves 20X and 35X speedup over off-body inference via bluetooth and on-body microcontroller based inference approach respectively. To the best of our knowledge, AI-On-Skin is the first ever wearable prototype to demonstrate skin interfaces with on-body neural network inference.

CCS CONCEPTS

• **Human-centered computing** → **Haptic devices; Gestural input; Ubiquitous and mobile computing systems and tools.**

KEYWORDS

Wearable Computing, Artificial Skin interfaces, Artificial intelligence accelerators, Neural networks, Handwritten text recognition

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1 INTRODUCTION

In recent years, artificial skin sensors have been designed for health monitoring [31], rehabilitation [6, 23], and as prosthetics [19]. Artificial skins for gaming and virtual reality applications have also been developed to serve as wearable skin input and feedback devices [12, 29, 32].

Smart skins provide immense amount of real time sensor data that is typically powered by AI for inferring useful information from the electronic skin. In recent years, artificial skin integrated with robots make use of CNNs [18, 24, 25], RNNs [24] as well as LSTMs [15] to achieve better touch sensing. Similarly, artificial skins use CNNs [9, 16] and RNNs [20, 33] for biomarker sensing [33] as well as gesture recognition [9, 16, 20]. Subramanian et al. [25] uses CNN on the frames obtained from a tactile glove based sensor array to learn human grasp. Dooyoung et al. [15] used an LSTM based DFM-Net for full-body motion tracking using a wearable sensing suit. Liu et al. [20] uses LSTM on the data obtained from a smart electronic skin to recognize hand gestures. Recently, an ultrasensitive electronic skin capable of detecting minute skin deformations [16] powered with a deep neural network identifies finger motions. U-net convolutional neural networks [9] were used for reliable detection of multiple touch points from electrical impedance tomography based artificial skin sensor.

Clearly, there has been an increasing use of neural network based inference integrated with current artificial skin sensors in various applications ranging from robotics to health monitoring. However, due to a lack of on-skin compute, current skin sensors have to rely on off-body computers such as phones and cloud servers, for compute. This causes a significant slowdown in real time response. While most existing wearable artificial skins can detect continuous touch, they cannot perform practical real-time recognition tasks that require not just sensing, but computing and responding, such as handwriting gesture recognition using deep learning because they lack on-skin compute. For instance, for a person with a prosthetic arm, on-skin neural network compute can enable data from the skin-on interface integrated with his/her haptic arm to respond to touch, pressure, heat etc in real-time. We thus see a need for a fast, low-power on-skin AI compute engine (neural network accelerator) to be integrated with current artificial skins. In addition, the on-skin AI compute engine has to be highly configurable, so it can run diverse neural networks, and support multiple applications. More recently, Gordon et al. [8] demonstrated autonomous humanoid robots equipped with full body artificial skin which will enable sensing its entire body. In future, we can expect full-body worn artificial skin comprising of multiple skin patches embedded into textiles for enabling full-body sensing in health monitoring, virtual reality, robotics etc. Hence, on-skin compute should be able to scale to support full-body artificial skin, motivating for the need for a scalable, distributed architecture of skin sensor patches tied to AI compute engines capable of communication with adjacent skin patches.

In this paper, we demonstrate AI-On-Skin - a wearable prototype comprising artificial skin sensor patches integrated with a low power, software-reconfigurable, scalable neural network accelerator (which can be realized on FPGA or as an ASIC chip). AI-On-Skin can scale across the entire body - thereby allowing for faster

communication of neural network inferences across multiple artificial skin patches to achieve AI powered full-body artificial skin.

2 BACKGROUND AND MOTIVATION

This paper focuses on artificial skins, and thus, our literature review in this section will first survey notable artificial skin sensors, based on the following aspects - scalability of the skin sensor to the entire body, real-time sensing, power consumption, and the support for on-body compute capacity. We will then delve into the alternative ways of supporting AI compute for skin sensing applications today, highlighting the deficiencies, and motivating the need for AI-on-Skin.

2.1 Artificial skin sensors

DuoSkin [13] presents a simplified fabrication process to create customized functional stickers capable of customized touch detection. Nevertheless, it cannot continuously cover a large skin surface. SkinWire [14] demonstrates a on-hand gestural interface composed of IMUs placed on various locations on the hand connected via skin conformable wiring to a small central microprocessor. It can be powered by just a 27mAh rechargeable battery. SkinWire is not scalable across a large skin surface since it would require many IMUs to be wired on the skin surface. SkinMorph [12] is an on-skin interface that can tune its texture to serve as a wearable skin input. It consumes a high continuous current of 1A. Multi-Touch Skin [22] is a thin, flexible sensor capable of detecting high resolution multi-touch to provide on-skin interactions. It supports real-time sensing (100 touch detections per second) and scales across a large skin surface, but requires $\geq 1\text{mA}$ for each scan of the capacitive touch. SkinMarks [30] are skin-worn, highly conformable I/O devices composed of touch-sensitive electrodes. As they only work on curved body landmarks, they are not suitable for full body sensing. ACES [19] is an electronic skin capable of detecting touch in 60ns, 1000X faster than the human nervous system at low-power (7mW) and can scale over the entire body. For computation of each skin patch, ACES relies on Intel's SNN based Loihi [26] accelerator which uses conventional CPU cores and thus incurs high average power of 1.4W which is expensive to realize on body.

Table 1 summarizes these recent state-of-art artificial skin sensors/interfaces based on the above aspects. None of the above related works have on-body compute, instead relying on external compute devices for computing on their sensed data. As we will next motivate, on-body compute is necessary in order to realize practical, real-time interactive applications on artificial skins, as the delay and power involved in communicating sensed data to an external computer and back is exorbitant.

2.2 Alternative AI Compute architectures for Artificial skin interfaces

In this section, we explore alternative ways of realizing off-body and on-body AI compute for artificial skin, and discuss their tradeoffs in real-time response, scalability, communications and power.

2.2.1 Off-body compute via bluetooth. Figure 1(a) shows an off-body compute architecture in which each artificial skin sensor is

Table 1: Prior electronic skin sensors and AI-on-Skin

Technique	Scalability	Real-time sensing	Low-power consumption	On-body compute capability
DuoSkin[13]	✗	✓	✓	✗
SkinWire[14]	✗	✓	✓	✗
SkinMorph[12]	✓	✓	✗	✗
Multi-Touch Skin[22]	✓	✓	✗	✗
SkinMarks[30]	✗	✓	✓	✗
ACES[19]	✓	✓	✓	✗
AI-on-Skin	✓	✓	✓	✓

equipped with bluetooth via which the touch data is sent to a mobile or PC edge device for neural network inference and the inference is being sent back. This architecture is the most common since edge devices like mobile phones, tablets or laptops are pervasive and have high compute capabilities for performing fast neural network inference. However, bluetooth-low-energy (BLE)’s response time is slow, as bluetooth transmission and reception are dependent on the connection intervals. The recommended low-power connection intervals for bluetooth is 100ms [1]. So the BLE transmission and reception alone will take $100+100\text{ms} = 200\text{ms}$, which is already longer than the human touch reaction time of 150ms, even before any computation. Besides, BLE’s wireless transmission consumes high power of 1-25mW [11].

2.2.2 On-body centralized compute. Figure 1(b) shows a simple design in which multiple electronic skins connect via long wires to a centralized on-body computer which performs neural network inference. Wearable on-body compute can only support a light-weight battery and so, an energy-efficient microcontroller is a more suitable choice than higher-end mobile processors. This architecture requires multiple I/Os on the microcontroller depending on the number of artificial skin patches to be interfaced. Also, long wires from multiple artificial skins will have to interface with the central microcontroller. In terms of response time, most microcontrollers are able to perform neural network inference. Using CMSIS-NN on ARM Cortex M-7 running at 216MHz, it takes 99.1ms [17] ((excluding I/O communications and sensor data acquisition delay) to classify CIFAR-10 images using a three layer CNN. Also, STM32F746 [7] inferring the same three layer CNN architecture with a ARM cortex M-7 running at 288MHz and tensorflow takes 165ms. Real-time sensing, compute and response will thus be difficult to realize within the human touch reaction time of about 150ms[2].

2.2.3 On-body AI-On-Skin distributed compute. Both the previous architectures suffer from the following disadvantages: (1) They cannot achieve real-time touch response close to human reaction time. (2) They are not particularly suited for scaling to cover the entire body. (3) They have higher power consumption which reduces the battery life of the entire wearable artificial skin. In order to tackle the aforementioned challenges in integrating on-device compute capabilities to artificial skin interfaces, we propose a distributed on-body architecture, which sprinkles ultra-low-power AI accelerator chips across the body, each attached to a skin sensor, and computing AI inference across the whole body. Figure 1 shows

our on-body AI-On-Skin architecture where each artificial skin sensor patch is connected to a local neural network accelerator chip computing neural network inference and returning the inference results to skin sensor for fast response. In this architecture, the AI compute is distributed since each artificial skin sensor patch has its own neural network accelerator and adjacent sensor patches can communicate easily via their neural network accelerator. This helps to achieve a highly scalable and distributed wearable full-body worn artificial skin with multiple artificial skin sensor patches communicating across each other. Since each artificial skin sensor patch is only connected to its nearest neighbors, this architecture requires few short wires which reduce the transmission power.

Custom-designed AI accelerator chips, termed NPUs by Apple, are now commonly used in mobile phones and laptops for speeding up neural network inference [21]. For AI-on-Skin, in order to achieve the ultra low power required for a wearable, we chose an open-source spiking neural network (SNN)-based accelerator [5, 28], instead of the artificial neural network (ANN)-based accelerators that are more common in industry which are targeted for video and camera inputs. SNNs process discrete spikes and are well suited to process touch event data sent by artificial skin sensors. They offer very low latency, low power consumption and high temporal resolution, suitable for on-body deployment.

3 PROPOSED SYSTEM

3.1 Overview of AI-On-Skin

We first begin with a high-level overview of how a single artificial skin sensor patch (AI-on-Skin patch) can be trained to run a neural network model before extending it to our full-body worn AI-on-Skin architecture consisting of multiple AI-on-Skin patches. Figure 2 shows how a user writes on a single AI-on-Skin patch for handwritten English alphabet recognition. It consists of two phases – the *Training phase* where the neural network model for handwritten English alphabet recognition is trained and AI-on-Skin is configured to fit the specific neural network model (layers, neurons, synapses), and loaded with the trained weights; and the *Inference phase* when AI-on-Skin performs real-time inference of the handwritten alphabets.

During the training phase, we collect multiple labelled samples (sufficient for training the neural network model) of handwritten English alphabets from the artificial skin sensor. The labelled data is used to train a neural network architecture on a PC or server using well-known deep learning libraries such as keras, PyTorch

Recognition App.png

Figure 2: AI-On-Skin Workflow for English alphabets recognition

to obtain the trained model parameters. The trained model is then fed into our AI-on-skin software mapper which configures the neural network accelerator hardware to run the model. Our software mapper performs the following operations - (1) It takes in the final model parameters and converts it into a spike neural network (SNN) model parameters as our neural network accelerator is based on SNNs. (2) It generates the ASIC/FPGA configuration bitstream from the SNN model parameters. The bitstream is then flashed into the neural network accelerator. AI-on-skin is now configured and ready for use.

During actual use of AI-on-skin, a user can write letters on the AI-on-skin patch, which will lead to touch data being sensed and input to the AI-on-skin accelerator. The preconfigured accelerator will now run in inference mode, computing the neural network given the trained weight and incoming touch data spikes, to infer the specific handwritten alphabets written on the artificial skin sensor.

3.2 AI-On-Skin Prototype Design

We have developed a hand-worn wearable artificial skin based prototype, AI-On-Skin capable of performing on-body neural network inference. We chose the hand as the form factor for our prototype because of the increasing use of artificial skin interfaces on hand. Our AI-On-Skin approach can be readily modified to fit to any part of the body. Figure 3 shows photos of our prototype where each AI-on-skin patch comprises (a) MUCA [27] artificial skin-on interface equipped with a MUCA capacitance board, (b) I2C to UART interface to send data from the MUCA capacitance board to the CMOD A7 FPGA, (c) GPIO interface between two patches' FPGAs and (d) showing how our prototype is being worn. In this prototype, we have used one of the smallest FPGA development board CMOD A7 [10] to perform neural network acceleration. We just taped out

and fabricated our neural network accelerator as an application-specific integrated circuit (ASIC) so that an even more streamlined form factor can be realized at lower power in the future.

Our AI-on-skin's MUCA artificial skin interface comprises of an array of 12X21 touch points - each of the touch points are placed 8mm apart. The entire artificial skin interface is approximately of 17cm X 10cm dimensions, though the design can be readily scaled to larger dimensions. Multiple of these AI-on-skin patches can be connected to cover the entire body.

4 RESULTS

4.1 Handwritten word, letter and gesture/shape recognition with AI-on-Skin

We prototyped the following applications with AI-on-Skin patches : (1) Handwritten English alphabet recognition (2) Handwritten fixed length words recognition (3) Handwritten gesture/shape recognition. For each of the above applications, we collected the touch data via UART and trained an offline model using PyTorch. The trained model is then fed as input to our AI-on-Skin software mapper which converts it into a bitstream with configuration signals for the Shenjing AI accelerator implemented on FPGAs. The neural network was trained with the handwritings of a single user and during testing, the same user performs live handwriting on the AI-on-skin prototype. Table 2 shows the corresponding model architecture, number of FPGAs and inference accuracy for the above mentioned AI-on-Skin applications.

4.1.1 Handwritten English character recognition. We demonstrated the effectiveness of our AI-on-Skin prototype in inferring handwritten 26 English alphabets. We collected 100 input handwritten samples per alphabet and hence, the input training data consisted of $100 \times 26 = 2600$ input samples. We trained the neural network architecture shown in Table 2 consisting of 6 layers. We tested our

Figure 3: Components of our AI-on-Skin prototype - (a) MUCA artificial skin interface equipped with a MUCA capacitance board (b) I2C to UART interface to send data from the MUCA capacitance board to the CMOD A7 FPGA (c) GPIO interface between two patches' FPGAs and (d) AI-on-Skin prototype worn on hand with all the hardware components housed beneath the skin

Table 2: Neural network architecture and inference accuracy for AI-on-Skin applications

Model Type	Character recognition model	Three letter word recognition model	Gestures/shape recognition model
Model Architecture	Input (12X21) Convolutional layer (3X3 kernel) Pooling layer (2X2) Convolutional layer (3X3 kernel) Pooling layer (2X2) Fully connected layer (200 neurons) Fully connected layer (26 neurons)	Input (12X21) Convolutional layer (3X3 kernel) Pooling layer (2X2) Convolutional layer (3X3 kernel) Pooling layer (2X2) Convolutional layer (3X3 kernel) Pooling layer (2X2) Fully connected layer (256 neurons) Fully connected layer (40 neurons)	Input (12X21) Convolutional layer (3X3 kernel) Pooling layer (2X2) Convolutional layer (3X3 kernel) Pooling layer (2X2) Convolutional layer (3X3 kernel) Pooling layer (2X2) Convolutional layer (3X3 kernel) Pooling layer (2X2) Fully connected layer (256 neurons) Fully connected layer (256 neurons) Fully connected layer (15 neurons)
Number of FPGAs	2 (4 neuron cores)	3 (5 neuron cores)	4 (7 neuron cores)
ANN Accuracy (%)	97.6	94.4	95.2
AI-On-Skin Accuracy (%)	96.7	93.5	94.6

Table 3: Time taken for inference by AI-on-Skin against alternative AI compute architectures

Application	Off-body compute via BLE timing (μ s)	On-body centralized wired compute timing (μ s)	On-body AI-on-Skin compute timing (FPGA) (μ s)
Handwritten alphabet recognition	52453 (1X*)	85324 (0.62X)	2500 (20X)
Handwritten word recognition	63250 (1X)	93453 (0.68X)	3200 (20X)
Handwritten shapes or gesture recognition	77245 (1X)	103574 (0.75X)	4100 (19X)

*X refers to the inference speed up achieved against off-body BLE compute setup

AI-on-Skin for live handwritten English alphabet recognition using the above model and obtained an overall inference accuracy of 96.7% for a total of 20 writings for each of the 26 alphabets. The same neural network model implemented using PyTorch on PC had a testing accuracy of 97.6%. Our AI-on-Skin had a small decrease $\approx 1\%$ in accuracy due to the conversion of ANN to SNN.

4.1.2 Handwritten fixed length words. We extended our single alphabet recognition to fixed length English words recognition. For our experiments, we developed a vocabulary based CNN architecture to classify four lettered English words. We randomly chose 40 four lettered English words for our experiments. A few examples of our words are - book, them, card, drag, grab etc. We collected 80 input handwritten samples per word and hence, the input training data consisted of $80 \times 40 = 3200$ input samples. Our neural network architecture in Table 2 consists of 8 layers. We tested our AI-on-Skin patch for live four lettered word recognition using the trained model and obtained an accuracy of 93.5% for a total of 20 writings for each of the 40 words. The same model running on a PC gave an accuracy of 94.4%.

4.1.3 Handwritten gesture/shape recognition. Finally, we demonstrate how AI-on-Skin can recognize user-friendly gestures as well as a few shapes. We trained our model to infer the following gestures and shapes - (1) Click (2) Right Swipe (3) Left swipe (4) Swipe up (5) Swipe down (6) Zoom-in (7) Zoom-out (8) Tap (9) Drag (10) Zigzag (11) Circle (12) Square (13) Triangle (14) Sine Wave and (15) Multi-touch. For our experiments, we utilized a CNN-based architecture to classify the above mentioned gestures. We collected 100 input handwritten samples per gesture/shape and hence, the input training data consisted of $100 \times 15 = 1500$ input samples. Our neural network architecture in Table 2 consists of 11 layers. We tested our AI-on-Skin patch for live gesture/shape recognition using the trained model and obtained an accuracy of 94.6% for a total of 30 writings per gesture, for each of the 15 gestures/shapes. The same model running on a PC gave an accuracy of 95.2%.

4.2 Performance comparison of AI-on-Skin against off-body computation via BLE

The key design goal of AI-on-Skin is to provide ultra low-power, fast, real-time inference. As a baseline for comparison, we prototyped a conventional off-body compute architecture via BLE. We interfaced our MUCA artificial skin interface to a bluno BLE beetle[3] equipped with a TI CC2540 chip. The touch data from the skin interface is sent via BLE to a laptop with 16GB RAM to perform neural network inference and the inference values are then sent back to the skin via BLE. For our BLE connection, we set a connection interval of 7.5 ms to enable faster communications. This would consume higher power though, compared to the recommended connection interval of 100 ms[1]. Table 3 shows average inference times for AI-on-Skin(t_{AI}) against off-body BLE compute(t_{BLE}) taken over 20 inferences for all three AI-on-Skin applications. It is clearly seen that AI-on-Skin prototyped on FPGA achieves an average timing improvement of 20X against off-body compute via bluetooth. We did not measure data acquisition delay and pre-processing time, since they remain constant for both AI-on-Skin compute as well as off-body compute via bluetooth.

4.3 Performance comparison of AI-on-Skin against on-body microcontroller

We also compared our AI-on-Skin accelerator against a low power microcontroller. We used a Teensy 4.0 board [4] with a Cortex M-7 microcontroller running at 216 MHz to perform network inference for all three AI-on-Skin applications. We used the same neural network model in Table 2 and implemented it on Teensy 4.0 using CMSIS-NN framework[17] from ARM. For the inference time computation, we measure the time taken for sending touch data to teensy followed by the time taken for the neural network inference by CMSIS-NN and the time taken for sending the inference back. Table 3 compares the inference time taken by on-body microcontroller against AI-on-Skin. Our measurements show that AI-on-Skin prototyped on FPGA achieves a speedup of $\approx 35X$ vs. on-body compute with microcontroller.

5 CONCLUSION

In this paper, we have motivated the need for on-body "AI-on-Skin" - AI computing that is integrated with artificial skins to achieve skin sensing, compute and response in real time, at ultra-low power. We built a working prototype that covers the entire forearm and recognizes handwritten characters, words, shapes and gestures at high accuracy. We compared our AI-on-Skin prototype against two baseline systems, one which sends touch data wirelessly via BLE off the body to perform the computation on a mobile device, and another which uses a single centralized microcontroller mounted on the body for inference. Our results show AI-on-Skin realizing order of magnitude improvements in performance. In this work, we have realized a single AI-on-Skin patch with the AI accelerator realized with FPGAs. We are currently working on building a full-body suit comprising multiple AI-on-Skin patches, with our AI accelerator fabricated as ASICs, communicating inferences across each other. This would offer orders of magnitude power savings over off-body BLE compute. We also plan to perform large scale user studies with our AI-on-Skin full-body suit. We envision AI-on-Skin opening up the possibilities of wearable skins, enabling continuous monitoring of our health and wellness, augmenting and interfacing touch, one of our most critical senses, with computing.

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