How many climb the matterhorn?

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Demo Abstract: How Many Climb the Matterhorn?

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ABSTRACT

In this demo abstract we present a custom-built low-power geophone sensor node which features on-device mountaineer classification using a convolutional neural network. The execution of such a processing-heavy algorithm on an embedded platform is enabled by optimizing the memory requirement of the neural network through advanced quantization and pipelining techniques. As a result, real-time classification with low energy consumption can be achieved.

CCS CONCEPTS

• **Information systems** → *Clustering and classification*; • **Computing methodologies** → **Neural networks**; • **Hardware** → *Sensor applications and deployments*; *Sensor devices and platforms*; • **Networks** → Wireless mesh networks; *Sensor networks*.

KEYWORDS

Natural Hazard Warning System, Wireless Sensing Platform, Embedded Convolutional Neural Network, Machine Learning, On-device Classification

1 INTRODUCTION

Intelligent sensors necessitate application specific data processing capabilities to be integrated as close to the data source as possible. This allows to trade off storage and bandwidth requirements with local processing that performs data transformations based on signal processing and decision making techniques. We have developed an event-triggered microseismic sensor that allows to capture geophysical signals precisely when it matters most, i.e. the input signal exceeds a pre-defined threshold and consequentially not wasting precious resources when nothing can be observed. The application of such sensors are passive monitoring of natural hazard sites, e.g. rockfall or their precursory signals [1]. By leveraging the theoretical concept of co-detection [1] on a large set of sensors we can compress the data obtained from many geophone sensors and transfer the detected events efficiently over a low-power wireless sensor network without the performance impairments of previous work [6]. However such a simple threshold triggering technique is not able to distinguish actual rockfall signals from noise sources. The data obtained contains true events as well as natural and anthropogenic noise. We therefore utilize machine-learning-based classification of the signals to actively identify humans walking through an instrumented hazard zone and remove these false positive warnings from the data. In this demo abstract we focus on the fact that the knowledge about mountaineer activity can additionally be used for information purposes (e.g. informing emergency services about path utilization as illustrated in Figure 1). In our work, running

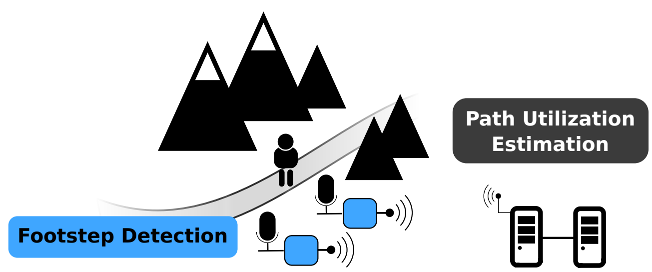

Figure 1: Illustration of an application scenario. Geophone sensor nodes are deployed in a high-alpine environment to surveil a hiking or climbing path. The timely information about path utilization is beneficial for emergency services as well as tourism statistics.

a convolutional neural network (CNN) on an embedded device is made possible by quantizing and pipelining the neural network inference resulting in a substantially reduced computing time and memory requirement. In this way, convolutional neural networks that would not run unmodified on a memory constrained device can be executed in real-time and at scale on low-power, off-the-shelf embedded devices. A field study with our system is running on the rockfall scarp of the Matterhorn Hörnligrat at 3500 m a.s.l. since 08/2018.

Complementary material related to this paper, such as code, is provided online [2].

2 MOUNTAINEER CLASSIFIER

The training of the convolutional neural network is performed offline using an openly available dataset [4, 5] resulting in a top error rate of 0.0240 and a top F1 score of 0.9779.

The implementation on the embedded device is subdivided into four steps which are data acquisition, pre-processing, classification with CNN and transmission. After data acquisition a pre-processing step is executed calculating a log-compressed time-frequency representation which is used as input to the convolutional neural network. In order to run the CNN-classifier on a low-power embedded device the algorithm's memory footprint must be reduced, which is performed by combining two strategies: (i) quantization of the neural network to allow parameters being stored in SRAM and (ii) distributing the computations into multiple computation cycles to enable SRAM only processing and to provide a low latency. The first strategy is performed using incremental network quantization [7] and reduces the size of the network's parameters by a factor of 4. The latter strategy is performed by using a novel method we coined time distributed processing [3]. Time distributed processing pipelines the inference by using a depth-first computation of the convolutional neural network and by exploiting the temporal characteristics of microseismic data. Effectively, the classification of a long input signal begins as soon as a short chunk is recorded. The convolutional neural network can be partially computed for this short chunk with reduced memory requirements while buffering intermediate results. Consecutive short chunks are processed until classification of the long signal can be established based on the precomputed intermediate results. As a result, the inference time and the inference memory requirement can be reduced and can be kept constant regardless of the temporal size of the convolutional neural network input.

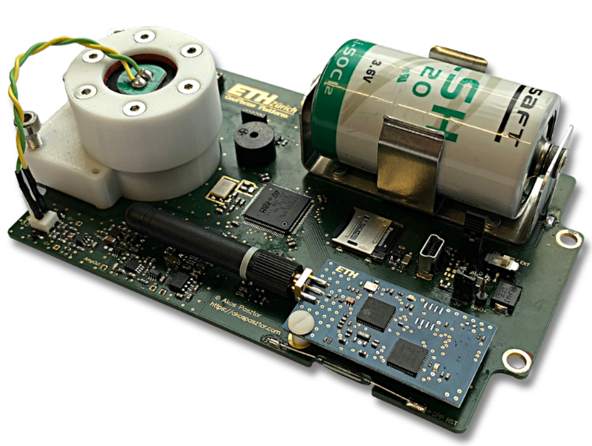

Figure 2: Image of the battery-powered geophone sensor node. The node is a custom-designed realization of the dual processor platform[2] and includes a geophone sensor, an analog low-power threshold-based wake-up circuit, an ARM-Cortex M4 application processor and a CC430-based communication board. This demo only utilizes the application processor.

3 DEMONSTRATION SETUP

The capabilities of the on-device mountaineer classifier are demonstrated using pre-recorded data from the Matterhorn field-site deployment and one geophone sensor node (Figure 2). The microseismic stream accompanied by time-lapse images are visualized in real-time on a screen. The microseismic stream will be pre-selected to contain a representative distribution of silent periods and periods of mountaineer activity over the course of a day. Since we cannot replicate the field-site scenario, only a digital signal is used and the sensor node's analog frontend (geophone sensor and analog triggering circuit) is bypassed. The laptop is used to emulate the analog triggering circuit and to segregate the microseismic stream into threshold-triggered events which are sent to the geophone sensor node to be further classified by the previously presented on-device mountaineer classifier. The classification result (mountaineer yes/no) is illustrated by LEDs on the geophone sensor node and displayed on the screen. The event length and inference time with/without time distributed processing will be highlighted given the microseismic stream visualization. The audience is able to verify the classification accuracy by checking the time-lapse images for mountaineer presence. Furthermore, statistics about the path utilization since demo start are displayed on the screen.

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[2] See IPSN 2019 demo abstract about the dual processor platform by J. Beutel et al.