ICIS 2019 Proceedings | Mobile, IoT and Ubiquitous Computing

Augmented Intelligence for Quality Control of Manual Assembly Processes using Industrial Wearable Systems

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Short Paper

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Abstract

Empowered by machine learning and artificial intelligence innovations, IoT devices have become a leading driver of digital transformation. A promising approach are augmented intelligence solutions which seek to enhance human performance in complex tasks. However, there are no turn-key solutions for developing and implementing such systems. One possible avenue is to complement multi-purpose hardware with flexible AI solutions which are adapted to a given task. We illustrate the bottom-up development of a machine learning backend for an augmented intelligence system in the manufacturing sector. A wearable device equipped with highly sensitive sensors is paired with a deep convolutional neural network to monitor connector systems assembly processes in real-time. Our initial study yields promising results in an experimental environment. While this establishes the feasibility of the suggested approach, further evaluations in more complex test cases and ultimately, in a real-world assembly process have to be performed.

Keywords: Internet of Things, Augmented Intelligence, Deep Learning, Machine Learning, Industrial Wearable Systems, Manufacturing

Introduction

Recent advances in sensor technology, a continuing decline of hardware prices and ubiquitous networking capabilities have led to significant growth in Internet of Things (IoT) devices and applications. Fueled by innovations in machine learning and artificial intelligence, these new IoT devices become a leading driver of the ongoing digital transformation and enable a plethora of autonomous systems (Gubbi et al. 2013; Patel et al. 2017). Driven by the digital transformation, an increasing number of tasks can be automated substituting human work and forcing workers to adapt to this changing environment. The impact of increasing automation has often been discussed controversially (David and Dorn 2013; Loebbecke and Picot 2015; Rajnai and Kocsis 2017) and is attracting significant media attention. Still, many tasks cannot be fully automated. A case in point are complex assembly processes which easily surpass motion capabilities of current robot generations (David 2015; Gibbs 2016; Pfeiffer 2016). In these settings, digital transformation is not about automation but rather about assisting and improving human performance through smart IoT devices. As pointed out by Pavlou (2018) and Pan (2016), human-computer symbiosis, also referred to as augmented intelligence, has the potential to leverage the complementary strengths of humans and computers. Thereby, augmented intelligence enhances human task performance. For example, Liew (2018) designs an augemented intelligence system for microsurgical procedures and Westerfield et al. (2015) utilize intelligent tutoring systems to train their workers.

However, there is no one-size-fits-all solution to develop and implement augmented intelligence systems. As smart IoT devices have to be newly developed or at least redesigned for many use-cases, the unique combination of hardware (sensors, motors, signals) and data processing during highly specialized processes will most of the time limit the direct applicability of existing training data or pre-trained machine learning models.

By means of a use case from the manufacturing sector, we illustrate the bottom-up development process of an augmented intelligence system and highlight the critical steps as well as the obstacles. Specifically, we design a wearable device for real-time quality control in an electronics assembly production step. Our example application seeks to detect if connector systems (plugs) are properly connected during a manual assembly process. Such manual processes are prone to human errors. In response companies strive to design fail-safe production processes. A case in point are simple but yet effective “Poka-Yoke” mechanisms (Dvorak 1998). Such mechanisms ensure that errors and defects are identified and eliminated at the source (“built-in” quality). In turn the cost of quality control can be reduced significantly. This is achieved either through fail-safe mechanisms or direct feedback of successful completion.

A common variant of such a feedback Poka-Yoke implementation are connector systems that mechanically emit a distinctive acoustic signal (“click”) to signify successful connections. However, such connections often have to be made under aggravated circumstances and outside a worker’s line of sight (e.g., plugs have to be connected behind the glove compartment or in the drivetrain) while loud ambient noises overpower the click sound. Consequently, neither visual nor acoustic feedback mechanisms are applicable. One way to overcome this obstacle is to augment the worker utilizing a multi-use structure-borne noise sensor which can detect object vibrations beyond superhuman levels. Such sensors can be embedded in a wearable device which is positioned at the workers’ wrist (close enough for reliable detection, not impairing assembly motions). The device can then continuously record a broad band of frequencies transmitted via air (acoustic signals) or vibrations (structure-born noise). This hardware needs to be paired with an analytic backend that identifies valid click sounds from the sensor data stream. In turn, the system can offer direct feedback concerning the success of connections. Figure 1 illustrates a prototype of this IoT device.

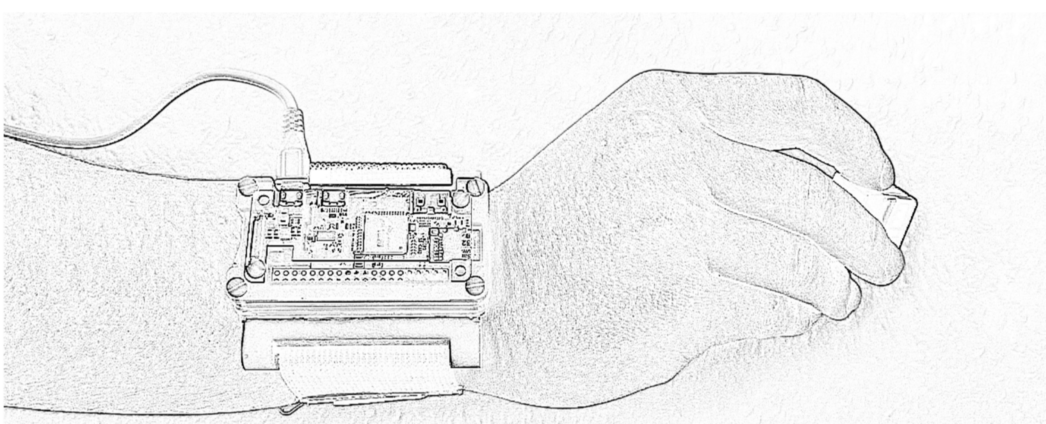

Figure 1. Prototype of the Wearable IoT Device

Related Work

Already in the early 2000s, Stanford (2002) showcased the deployment of wearable computing solutions in industrial environments. He characterizes multiple wearable computing projects. One of these early projects was Boeing's pioneer work on wearable-computing-based guided assembly (Mizell 2001). By recording test results, this wearable smart device helped mechanics working on planes during assembly. More recent work focuses on wearable solutions for industrial maintenance (Zheng et al. 2015), which enables an efficient way for collaborating with remote expert technology. Another approach builds a wearable device securing a safety system for the mining industry (Mardonova and Choi 2018). In particular, they are using a sensor-equipped smart safety vest, eyewear, and smart helmet for real-time measurements of environmental conditions and the miner's health. Not putting special focus on wearables, Stein et al. (2018) highlight to what extent manual leakage detection for vacuum injection molds can be assisted by sensor data and spatial prediction models—another instance of augmenting worker capabilities employing intelligent systems. Kong et al. (2018b) classify such systems as Industrial Wearable Systems. Such systems adopt a common design blueprint: data collection from equipment, human-machine cooperation, intervention, and control of equipment.

In order to set up our system, we need to integrate our wearable computing sensor and a model classifying the recorded stream. This model not only needs to identify the attributes of the specific noise but also distinguish it in different environments. The literature discusses different approaches for sound classification. Hidden Markov Models have been the classic approach to classify acoustic signals (Su et al. 2011). These models allow to map individual parts of the sounds to states and compare them. More recently, machine learning approaches such as random forest tree classifiers (Saki and Kehtarnavaz 2014) and Support Vector Machines (Wang et al. 2006) are successfully applied for this task. With the rise of deep learning, more recent studies focus on sound classification through Recurrent Neural Networks (Vu and Wang 2016). Such networks are mainly used in the field of speech recognition, which is closely related to noise detection (Graves et al. 2013). Finally, most recent work discusses the classification by utilizing deep convolutional neural networks (CNN) (Li et al. 2018; Salamon and Bello 2017; Zhu et al. 2018). According to Mesaros et al. (2018), CNNs form the best basis for the classification of sound. The cited publication represents the "IEEE AASP Challenge on Detection and Classification of Acoustic Scenes and Events" (DCASE) 2018 challenge. Since 2013, the DCASE competition aims to continuously support the development of computational scene and event analysis methods by comparing different approaches using common publicly available benchmarks (Giannoulis et al. 2013). It is a well-known challenge in the sound classification research community presenting state-of-the-art architectures.

Conceptual Approach

We seek to complement wearable sensor equipment with a data analytics backend to establish a real-time quality control system. To this end, we follow the Design Science Research paradigm, which puts forward the development of useful artifacts as the central research goal (Baskerville et al. 2018; Von Alan et al. 2004). Such artifacts can either embody (i) new solutions for known problems, (ii) known solutions extended to new problems, (iii) new solutions for new problems, or (iv) known solutions for a known problem (Gregor and Hevner 2013). Along these lines, our artifact instantiates as a new solution for a known problem as we combine existing components from different domains (information systems research, artificial intelligence) to a well-known problem from quality control. Gregor and Hevner (2013) refer to such an artifact as improvement.

The structure-borne noise sensor, combined with a Raspberry Pi module, is worn on the worker's wrist without restricting mobility. The device continuously streams sensor readings to a server using the Message Queuing Telemetry Transport protocol (MQTT), one of the standard IoT communication protocols (Al-Fuqaha et al. 2015). The predictive backend queries the data preparation module every second using the last five seconds of recording data. Based on the prepared data, the classification module provides real-time feedback to the worker. The architecture of our artifact is sketched in Figure 2.

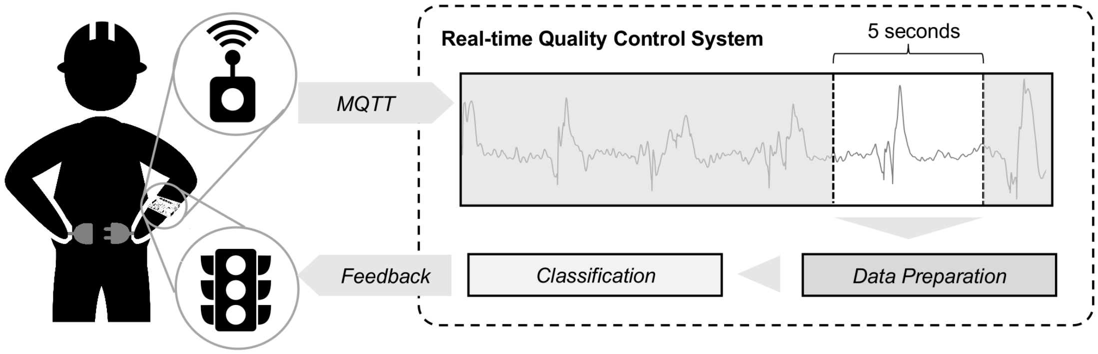

Figure 2. Artifact Architecture

Experimental Design and Data Collection

Following Basili (1996), the quality and efficacy of a system have to be rigorously demonstrated by means of an appropriately selected evaluation method. While we aim to evaluate the artifact in a real production environment, we first have to show its viability. Hence, our initial case study relies on an experimental replication of the real-world assembly process.

To collect sufficient training data, we created a training program which repeatedly instructs the test person to perform one of the following actions in the next five seconds:

- Assemble the plug appropriately and thereby generate a positive example.
- Perform some kind of different movement and generate a negative example.

In order to ensure a similar distribution of the environmental sounds, the program randomly selects the action to be performed. Note that we opted for oversampling of negative examples as there is only one way to successfully connect the plugs but many ways to generate non-successful sounds (incomplete clicks, drops, walking, speaking, background noise).

Following this procedure, we collected a data set of 4,375 samples (1,525 positive and 2,850 negative). Each five-second sample comprises an array of 160,000 sensor readings as well as a binary label (positive or negative). Figure 3 visualizes two examples of raw data. In the right panel, a "click" is located between the two vertical dotted lines. Comparing the two samples, it becomes obvious that there is much noise in the data and that the correct assembly of the connector systems cannot readily be identified from raw data.

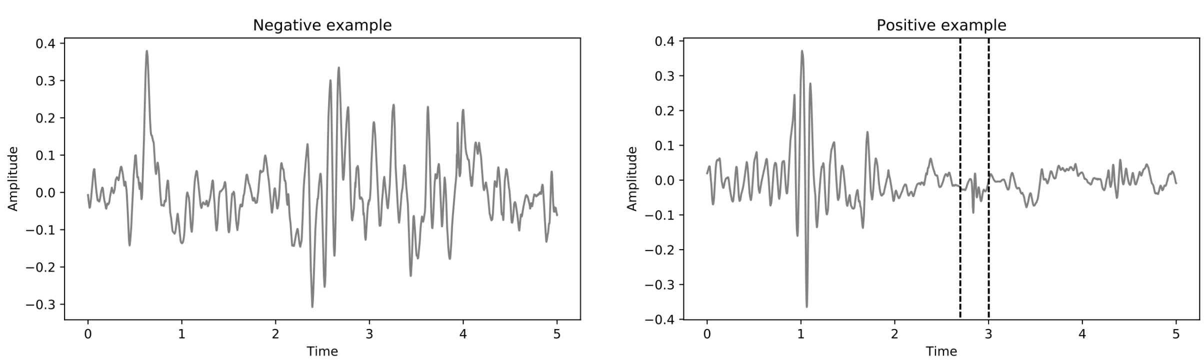

Figure 3. Raw Data

Data Preparation and Modelling

We apply a deep convolutional neural network to classify whether or not a given sound sequence corresponds to a correct assembly of the plugs. In-line with Agarwal and Dhar (2014) call to action we primarily focus on problems and outcomes while limiting development efforts for new algorithms. Thereby, we follow Griebel et al. (2019) and do not design new network architectures from scratch but select one from state-of-the-art research papers solving similar problems.

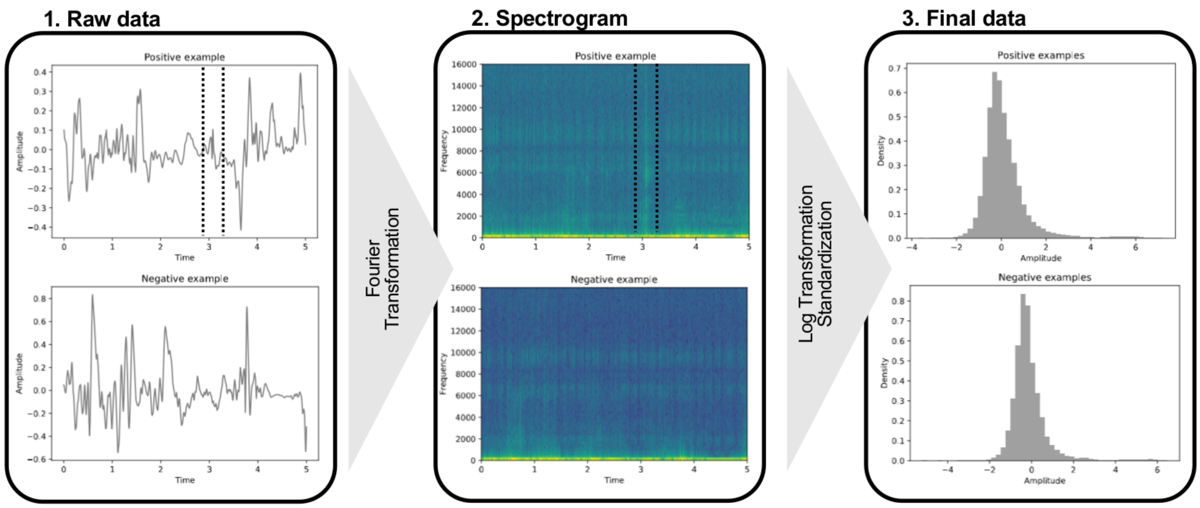

Figure 4. Data Preparation Pipeline

Data Preparation

Even though CNNs render the task of manual feature engineering obsolete, the raw data still needs to be transformed in order to train meaningful models effectively.

On the one hand, network architectures for sound classification are designed to classify an acoustic signal based on its frequency spectrum. To obtain this, we decompose each recorded five-second time window into its individual frequencies utilizing the short-time Fourier transformation (Sejdić et al. 2009). This transformation splits a function of time (the sensor readings) into its frequencies (Bracewell and Bracewell 1986). Performing the Fourier Transformation on our one-dimensional raw sensor data returns a two-dimensional spectrogram. On the other hand, neural networks converge faster and therefore perform better if the input variables follow a standard normal distribution (LeCun et al. 2012). Hence, we perform a log transformation on the spectrogram and subsequently standardize the input variables. Figure 4 shows the data preparation pipeline on a negative as well as on a positive example.

Modeling and Training

As stated above, DCASE provides best practice models for sound classification. Therefore, we adopt the current DCASE-19 baseline model (Kong et al. 2018a), which proved to be successful in the 2016 DCASE challenge (Valenti et al. 2017), to tackle the classification problem at hand. This CNN comprises two convolutional layers and one dense layer, followed by a sigmoid binary classification layer. For regularization, we included batch normalization (Ioffe and Szegedy 2015) after each convolutional layer and dropout (Srivastava et al. 2014) after all layers. We refer to Valenti et al. (2017) for a visual illustration of the CNN and additional details on the network.

In order to avoid overfitting, we split our data into a training set (3,500 samples ~80%) and a test set (875 samples ~20%). This is done in a stratified manner, maintaining the ratio of positive and negative samples from the original data. We additionally draw a random validation set (350 samples) from the training data to monitor the performance during model training and tuning. We preserve the test set for the final evaluation.

To increase generalizability as well as training stability, data augmentation is commonly applied to train deep neural networks. For image recognition tasks, this involves random transformations of each image such as rotation, shearing, or flipping. In contrast to images, a spectrogram carries different information on each axis (frequency, amplitude, and time). Hence, we can only apply transformations that do not change the sequence of the data. This renders the addition of Gaussian noise to each training sample as a valid remaining option for our case.

We implement the final model using the Tensorflow framework (Abadi et al. 2015). The training is performed on an Nvidia Tesla P100 GPU to minimize the binary cross-entropy loss by means of the Adam optimizer (Kingma and Ba 2014).

Preliminary Results

We implement different state-of-the-art audio classification approaches to assess the performance of our CNN. In contrast to deep neural networks, these models are based on hand-crafted features. To this end, we extract 645 features from the spectrogram, namely the arithmetic mean, minimum, maximum, and median value for each frequency. We chose four different baseline models. These comprise two tree-based ensembles, a gradient tree boosting (XGB) (Chen and Guestrin 2016) and a random forest (RF) (Breiman 2001), as well as a support-vector machine (SVM) (Cortes and Vapnik 1995) and a Gaussian naive Bayes classifier (GNB) (Chan et al. 1982).

We chose the following evaluation metrics considering the class imbalance (more negative than positive samples) in our data set:

- *Matthews correlation coefficient* (MCC) is generally regarded as a good measure for imbalanced data (Powers 2011). It takes true positives (instances of correctly classified properly connected plugs), false positives (instances that contain falsely connected plug events but are erroneously classified as properly connected), true negatives (instances of falsely assembled plugs classified as falsely assembled plugs), and false negatives (instances of properly assembled plugs that are erroneously classified as falsely assembled) into account.
- *Precision* reports the fraction of correctly classified correctly assembled plugs among all instances that are classified as correctly assembled, i.e., true positives divided by the sum of true positives and false positives.
- *Recall* indicates the fraction of correctly assembled plugs that are correctly classified (true positives) among all correctly assembled plugs (true positives and false negatives).
- *F-Measure* considers both precision and recall. It is calculated as the harmonic mean of the Precision and Recall criteria.

Model	MCC	Precision	Recall	F-Measure
CNN	**98.74 %**	99.67 %	**98.69 %**	**99.18 %**
XGB	92.93 %	96.32 %	94.43 %	95.36 %
RF	90.98 %	98.56 %	89.51 %	93.81 %
SVM	76.58 %	**100.00 %**	68.52 %	81.32 %
GNB	25.22 %	39.12 %	99.67 %	56.19 %

Table 1. Classification Results on the Test Data

As depicted in Table 1, the CNN achieves the best overall performance with an MCC of 98.74%, surpassing the second-best model (XGB) by 5.81%. Notably, the SVM yields a precision of 100% (CNN 99.67%). It flawlessly classified all correctly assembled plug instances as correctly assembled. This can be particularly interesting for quality control systems that require high reliability. However, such systems should preferably yield a high recall as well. This holds true for the CNN, but not for the SVM.

Expected Contribution and Future Work

Our ultimate goal is to create an industrial wearable system to support quality control in connector systems assembly. By combining a hardware solution with a convolutional neural network, we can perform real-time classification of assembled plugs based on structure-borne noise signals. Our initial study yields promising results and establishes the feasibility of the suggested approach. Furthermore, our artifact serves as a blueprint for similar IoT applications. Traditional audio classification methods require custom data pre-processing and extensive feature engineering. In contrast, our approach can quickly and flexibly adapt to new conditions in an automated pipeline by requiring only new training data for training or fine-tuning.

However, our initial findings are limited as the study was performed only on a single plug and on data collected by a limited number of test persons. We identify future research opportunities in various directions. Going forward, we plan to expand our test setting to more complex scenarios using different plugs and additional test persons. In particular, we want to quantify how much training data is needed to reliably adapt the neural network to changing conditions (i.e., different workers, different environments, different connector systems). This is of particular interest for companies planning to use such a system as test data collection is time-consuming and expensive. We posit that the additional data requirements can be limited by leveraging transfer learning principles which allow CNNs to adapt to related tasks efficiently.

Following Nunamaker Jr et al. (1990), evaluating the practical utility of the proposed artifact in the described experimental environment would already be a contribution to the research community. Going even further, the feasibility of the artifact should also be evaluated in a real-world assembly process (Sein et al. 2011). Thereby, not only the performance of the neural network but also the user behavior should be analyzed. Leveraging the constructs put forward by Venkatesh et al. (2003), valuable information regarding the development and deployment of the proposed information system can be derived from the user behavior.

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