Towards supervised real-time human activity recognition on embedded equipment

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***Abstract*—In recent years, real-time human activity recognition (HAR) has reached importance due to its applications in various domains such as assistive services for the elderly in smart buildings, monitoring, well-being, comfort and security. Various techniques, researched within the image processing and computer vision communities, have been established to recognize human activities in real-time, but all of them are based on wearable sensors and there is no much attention for ambient sensor based approaches. In the literature, deep learning (DL) is one of effective and cost-efficient supervised learning model and different architectures haves been investigated for real-time HAR. However, it still struggles with the quality of data as well as hardware implementation issues.**

This paper presents two contributions. Firstly, an intensive analysis of DL architectures and its characteristics along with their limitations in the framework of real time HAR are investigated. Secondly, existing hardware architectures and related challenges in this field are highlighted (adaptation of DL architectures towards microcontrollers, difficulty to provide a smart home with numerous sensors and trends regarding cloud-bases approaches). Then, new research directions and solutions around the real-time data quality assessment, the study of main performance factors for DL on microcontrollers, the concept of minimal sensors set up for the employment of IoT devices and the distributed intelligence are suggested to solve them respectively and to improve this field.

***Index Terms*—smart building, real time human activity recognition, deep learning, software and hardware architectures, edge computing.**

I. Introduction

Occupant behavior has been shown to be one of the main factors explaining the discrepancy between simulated and actual energy consumption. Many scientific studies have been carried out on the subject of modeling the activities of occupants to reduce this gap [1], [2]. However, an activity is affected by different contextual elements specific to each household/building. To take this into account, stochastic approaches have been proposed with statistical data to model activity profiles according to household characteristics (occupants, type of building). Their results provide only average information, based on information collected on different households. Therefore, they are not specific and cannot be representative of the behavior of a particular household.

New buildings (residential, public or commercial) are generally equipped with an important number of sensors and smart meters, making them smart with improved opportunities and capacities. For instance, the main goal of the related applications to energy management systems is to decrease waste, mainly due to the irresponsible human behaviors [3]. Indeed, energy deficiency represents a global problem.

Nevertheless, energy usage is always in demand, particularly given the numerous technological progress that rely on electrical power for operating. The automatic depletion of energy consumption in buildings has received a lot of attention recently [4] and early try included automatic regulation of heating or light in building automation. However, these techniques were considered inappropriate due to unacceptable reaction to the occupants [5]. An important number of studies has shown the importance of putting the occupants in the energy-saving loop while ensuring their comfort [6]. Occupants' behavior has a major influence on building energy consumption [7]. Hence, there is a need to recognize human activities and quantify their impact on building energy use.

Authors of [8] highlighted three major benefits of the capability of modeling and recognizing occupants' activities earlier for energy simulation: improve services for users (assistance to the elderly people, comfort and health monitoring), support to building systems control measures and more realistic.

In recent years, many approaches have been proposed to recognize occupants' activities in residential buildings. Sensor-based approaches are the most popular to extract the patterns of activities from survey sensor data based on the characteristics (building type, age, job) of residential buildings. For a HAR task, a delay in the activation of sensors could affect the decision-making about activity. While a long delay may be acceptable for some types of activities, others require very short decision time in the event of an emergency, such as a resident falling. This is important for human activity recognition because getting the results in real time is an advantageous solution in many situations.

In the literature, machine learning is a favored approach as it deals with various applications of real-time HAR [3]. In particular, deep learning gains more importance due to its immense characteristics in language processing [9], data mining and image classification [10]. The remarkable growing of data and recent development in technologies have brought different key directions in deep learning models and makes the system to perform better than expeditious learning models.

However, it still struggles with numerous challenges. The

data variability is still an unsolved problem because sensor data are very sensitive to the localization of sensors as well as the house configuration. There is a need to (i) perform Fault Detection and Diagnostics (FDD) tools to detect drifts using artificial intelligence algorithms to solve the temporal drift, and (ii) the use of transfer learning algorithms to solve the variability of settings.

Multi-occupant and concurrent activities' recognition are the most challenged problems in human activity recognition task using ambient sensors. Modeling this type of activity as a multi-label classification problem or using CNN architectures could be an interesting alternative to deal with this type of activities.

Taking into account the quality of the training data was a problem rarely discussed in the literature. In fact, as the available information changes over time, the structure of the training data should also be readjusted to deal with such dynamic aspects and there is a need to use indicators to test the data quality, such as spread rate technique proposed in [11] which considers the global space of the data and does not look at each class alone.

The unavailability of sensor data over long periods of time, missing data as well as non-annotated events are also challenging ones. In this direction, there is a need to (i) take into account the missing data by adding a penalization function in the optimization algorithm when the data are not available, and (ii) to judge the performance of algorithms using evaluation metrics weighted by the number of representations in a dataset, F1 weighted score or balanced accuracy when the events are not annotated.

In this work, an overview about neural network architectures and hardware architectures in the field of real-time HAR is provided. Existing algorithms and related challenges in this field are firstly highlighted. Then, new research directions and solutions are suggested to solve them respectively and to improve this field.

The paper is organized as follows: Sections II and III investigate the software and hardware deep learning architectures in the framework of real-time HAR. A discussion and a conclusion are provided respectively in section IV.

II. Deep Learning Architectures

The recognition of daily activities of occupants consists on identifying the daily activities of residents in an indoor environment such as a home [12]. These activities include sleeping, bathing, cooking, sitting and eating. Recognition of such activities in real-time is of great importance for its applications in various areas such as care centers and building surveillance.

Recent advances in artificial intelligence have led to a new hype cycle around possible applications for smart homes, including activity recognition. The most efficient and popular artificial intelligence systems are based on neural networks (NNs). In the literature, various learning models have been used by researchers in the field of real time activity recognition. Generally, the learning involves creating a statistical or probabilistic activity model that is augmented with large training data. The task of the model is to learn and recognize patterns that differentiate various classes in the training data, and apply this knowledge for the prediction/classification of test data. For example, [13] proposed a HAR system for the elderly people that allows to understand activity patterns, help them to maintain an independent lifestyle and detect early symptoms of any abnormalities using PIR (Passive InfraRed) sensors, ON/OFF switch sensors, chair/bed position sensors and pressure sensors. Eight types of activities were taken into account (sleeping, kitching, relaxing, dining, bedroom, garden, leaving home). A conversion to a 2D grayscale image to be used as input to the CNNs (Convolution Neural Network) was made.

For feature extraction, DCNN and more specifically AlexNet was exploited for its ability to automatically extract features from the image by tuning parameters in its convolutional and pooling layers. AlexNet is one of the powerful pre-trained DCNNs that could be used for mining purposes. characteristics [14]. It contains an input layer followed by 5 convolutional layers, 3 pooling layers and 3 FC layers, and an output layer. The feature vector is obtained directly from fully connected layers, then used as input to the classifier.

The extracted feature vector is divided into sets of learning and testing. The classifier is first trained using the training set, and then it will be evaluated against the test set. Adaptive Boosting (AdaBoost) has been used as a classifier. It is one of the most commonly used classification algorithms with a relatively high degree of accuracy, simplicity of implementation, flexibility and high generalization performance [15]. One of the advantages of the AdaBoost is that it uses the functionalities of each class separately when using all the features may not be needed at this time, it adjusts the errors of weak classifiers, achieving high accuracy with much less tuning of other strong classifiers [16].

[17] also proposed a service in terms of HAR using temperature sensors and binary sensors such as motion and door contact detection. The data preparation step uses Natural Language Processing (NLP) encoding, which consists of processing sensor events as words and activity sequences as textual sentences. First, each activity sequence is extracted from the data set as NLP sentences. Thanks to the label provided by the dataset, it is possible to know the beginning and the end of each activity. A word consists of the sensor ID with its value (example: sensor M001 ON). Each word of the sequences is transformed into an index to be usable by a neural network. A particular CNN; the FCN (Fully Convolution Network) that contains only convolutional layers e.g., no fully connected layers for the classification part; is used in this work and specifically the same structure as [18] is adopted. After three convolution blocks, the features are fed into a GAP (Global Average Pooling) layer. GAP is a pooling operation designed to replace the FC layers in classic CNNs. The idea is to generate a feature map for each corresponding category of the classification task. The resulting vector is fed directly into the softmax layer to perform the final classification. The

advantage of this architecture consists in the fact that there is no parameter to optimize in the GAP, which avoids an over-adjustment at the level of this layer.

However, many challenges related to data quality remain in the deployment of CNN for HAR system; not only on sequence analysis but also on the identification of salient patterns of the signals. These trends are discussed below in details.

1) Challenges related to sequence analysis: Data quality assessment is a key component for CNN based application, since it can drive better modelling. However, the CNNs present challenges related to sequence analysis due to the impact of data sparsity and irregularity (effect on understanding of context and long-term reasoning). Data sparsity also makes it more difficult to manage the variability of smart home data across its various parameters.

The problem of taking into account the quality of the training data was rarely discussed in the literature. In fact, as the available information is dynamic and changes over time, the structure of the training data should be readjusted to deal with such dynamic aspects. In [19], the authors have evaluated big data quality using different factors: volume, completeness, accuracy, consistency, precision, distinctness, timeliness. An existing data quality method has been proposed in the case of classification in order to avoid having overlapping classes [20]. In [11], the data quality is evaluated using the concept of spread rate, which considers the global space of the data and does not look at each class alone. However, most of these techniques are offline. In this work, we are interested to an online evaluation of the database using the spread rate whenever new training data is introduced.

Another research direction consists to take into account the outlier detection and insufficiency of labeled data in the training data. We are motivated by (i) detecting ambiguous outliers in real time using deep autoencoding model, (ii) proving the performance of this proposition by experimental results and (iii) comparing with state-of-the-art existing methods. The deep auto-encoding model could be used also to pretrain a CNN. Since the model can learn the data distribution from the unlabeled data, it can prevent DNN from getting stuck on local optima.

2) Challenges related to the identification of salient patterns of the signals: In HAR, only a few parts of the continuous signal stream are relevant to the concept of interest (i.e. human activities), and the dominant irrelevant part mostly corresponds to Null activity. Considering the way human activity is carried out in reality, each activity is a combination of several basic continuous movements. Typically, a human activity can last a few seconds in practice, and within a second some basic movements can be involved. From the perspective of sensor signals, basic continuous motions are more likely to correspond to smooth signals, and transitions between different basic continuous motions can cause signal values to change significantly. These signal properties in HAR require the feature extraction method to be efficient enough to capture the nature of basic continuous motions, as well as the importance of combining basic motions.

To solve this problem, the architecture proposed by [21] consists of several shallow architectures, and each shallow architecture is composed of a set of linear/nonlinear processing units on locally stationary signals. When all shallow architectures are cascaded, the salience of signals at different scales is captured. It is used not only to break down a large and complex problem into a series of smaller problems, but more importantly to obtain a specific "variance" of signals at different scales. Here, the "variances" of the signals reflect the salient patterns of the signals. As indicated in [22], what counts for the generalization of a learning algorithm is the number of these "variances" of signals desired to obtain after learning.

The advantage of this architecture is that feature extraction and classification are unified in a single model so that their performance is mutually enhanced. The results obtained show that CNN training time is about 1 hour, while testing time is 8 minutes. On average, in one second, the CNN can predict 56 raw instance labels. Thus, the efficiency of CNN is quite good for real-time HAR.

The next section deals with trends regarding the implementation of these architectures on embedded equipment.

III. Hardware Architectures

In section II, different deep learning architectures for real-time HAR in smart homes are discussed. In addition, the remaining challenges in that field as well as new opportunities are presented. However, beyond the DNN (Deep Neural Network) architectures, the full deployment of smart home services depends also on the development of the hardware systems and the usability and acceptability of these systems by the users.

In this work, three implementation types are discusses: microcontrollers, the employment of IoT (internet of Thing) and distributed intelligence.

A. Microcontrollers and AI: the challenges of embedded deep learning

In the literature, an important number of research works focus on the embedded implementation of different neural networks for human activity recognition. For example, [23] presented a qualitative and quantitative evaluation of different multi-layer perceptron (MLP) and convolutional neural network (CNN) structures for HAR implemented on a low power ARM Cortex-M4F-based microcontroller. [24] made the design of an energy-efficient deep learning models for realizing efficient HAR for mobile applications. A lightweight framework for the deployment of low-power but accurate HAR systems for these devices is presented and implemented in a microcontroller. Also, computational cost and energy consumption, and how different system configurations and deep learning model complexity influence on that are analyzed. These challenges are discussed below in details.

1) Challenges related to energy consumption devices: Running deep learning models on embedded microcontrollers has serious advantages, but also limitations that experts are working to overcome. The program memory size and the MCU (Microcontroller Unit) RAM are typically much smaller, often measured in kilobytes [25]. Add to that, a lot of MCU devices are battery powered. So, energy-efficiency is a crucial concern. In addition, hardware accelerators and GPU (Graphics Processing Unit) are not typically included in MCU devices; which are subject to real-time requirements. If that is the case, nearly 100% of the MCU time cannot be spent on the inference, as a large safety margin must be left unallocated [23].

The question that arises is: given the adaptation of the deep learning ecosystem towards MCU and the more powerful models of MCU, does it make sense to implement a NN architecture on MCU? A priori, deep learning is expected to provide an increased classification accuracy and a simplified software architecture. Using neural networks allows simplifying the inference pipeline, as it eliminates the need to separate the steps of feature selection and extraction. However, these benefits must be balanced with decreased inference speed and energy efficiency.

2) Challenges related to system configuration and DL model complexity: Most applications of real-time HAR in buildings focused on HAR using wearable devices such as accelerometer data, and there is no much attention in the literature to the real-time HAR from ambient sensors and its implementation on MCU.

In this work, given the best accuracy given by CNNs for this application compared with other architectures, we are motivated by identifying the main performance factors for a CNN on microcontrollers. The identification include the architecture of CNN as well as enabling hardware optimized libraries like microcontroller instruction set, microcontroller clock frequency and finally NN quantization (i.e the process of approximating a CNN that uses floating-point numbers by a NN of low bit with numbers. This reduces both the memory requirement and computational cost of using NN).

Depending on the network architecture, other aspects, like hardware FPU (Floating-point unit), may also be important. For example, if hybrid quantization is applied or if network quantization is not used at all, then floating point operations are necessary, and FPU becomes important. To solve this problem, we plan to study the impact of the choices of CNN architecture aspects (convolution, stride length, filter dimensions and padding) on the performance and to investigate the exact conditions when hardware FPU is advantageous.

B. Employment of IoT devices

The development of IoT devices with the improvement in autonomy and accuracy, along with the reduction in their cost, will make them accessible to residential buildings. Smart home builder companies such as Delta Dore company need to provide an adequate HAR hardware kit. Recently, many achievements in emerging technologies and important improvements in computing systems and IoT protocols have accomplished the communication through different devices for real-time HAR [26]. For example, [27] developed a healthcare system based on IoT technology to provide pervasive human activity recognition by using data mining techniques. The proposed HAR model utilizes a data-set that contains vital signs recordings and body motion for ten occupants with a diverse profile while performing twelve activities. In [28], an active learning paradigms for analyzing human activities using Wearable Internet of Things (W-IoT) sensors for health parameter analysis is designed.

Despite cheaper actuators and sensors, it is very difficult to provide all the homes with a large set of sensors. This is a challenge. Therefore, a smart building system needs to optimize their hardware under number of occupants, building architecture and constraints of budget.

In this work, we are motivated by developing new tools to determine the most important sensors in an equipped smart home to be used for real-time HAR i.e a minimal sensor setup. A Principal Component Analysis (PCA) technique ([29], [30]) could be investigated to maintain information variability. Another research direction consists on developing cyber-secure systems.

C. Edge intelligence

The AI of the future must come out of the cloud to meet its users and overcome problems related to communication overload and data privacy. Hardware architectures for artificial intelligence (e.g. Neuro Processing Unit - NPU, IoT devices) are a key topic for new applications, embedded in low power and low latency devices.

Sensor-based techniques are the most known and used methods for real-time HAR. Most of the data collected through ambient sensors or wearable devices have a simple flow which consists of data pre-processing, data segmentation, feature extraction and modeling such activity (classification, prediction, detection). These techniques often require a dedicated infrastructure for computing [31]. The development of numerous AI based services in the field of IoT opened doors for cloud-based platforms [32]. However, power budget application, data collected through devices with limited bandwidth are the main challenges for cloud-based approaches [33]. Due to these application level limitations, the concept of Edge Computing is prospering [34].

Edge computing refers to technologies that enable computations to be performed at the edge of the network, on so-called "downstream" data on behalf of cloud services and other so-called "upstream" data on behalf of services IoT [35]. It is characterized by great autonomy, since it does not depend on the cloud or the server. It reduces communication latency, traffic network, communication costs and privacy issues. Also, edge devices are peripherals limited in resources and cannot take into account load high computational loads. Also, storing data locally risks data loss. Application of edge-computing concept to real-time HAR using only wearable sensors is

relatively a new research interest and only few works are present in the literature [31], [36].

In this research, we are interested in a novel edge computing system for real time HAR using ambient sensors in residential buildings. Many trends remain in the deployment of DL on the edge, not only on end devices, but also on the edge servers and on a combination of edge servers, end devices and the cloud. In the following, we discuss some of these trends.

1) Deep Learning Benchmarks on Edge Devices: An important number of research works has addressed deep learning operating at the edge of the network [37]. Natural language processing and computer vision were discussed as examples of application, with the common thread being the need for real-time processing of data produced by end devices.

Methods for accelerating deep learning inference on edge servers, cloud, and end devices have been described in [38]. These methods take advantage of the unique structure of neural network models as well as the geospatial locality of user demands in edge computing. Tradeoffs between time latency and accuracy have proven to be important factors in [39].

DL model training, where multiple end devices collaboratively train a DNN model (possibly with the help of an edge server and/or the cloud) was also discussed, including techniques to further improve privacy.

Many challenges remain, both in terms of privacy, resource management, performance improvements and integration with other networking technologies such as Soft Defined Networking (SDN). These challenges can be addressed through technological innovations in system design, algorithms, and hardware accelerations.

2) The energy system challenge: The minimization of energy consumption of deep learning is necessary for battery-powered edge devices (smartphones, for example). While lowering the amount of computation implicitly decreases energy consumption, understanding the interactions of the DL computations with other mechanisms of battery management, such as the optimization of sensor hardware or CPU throttling [40], is an important research field.

In conclusion, in order to decrease the frequency of deep learning executions and consequently the overall energy consumption, it is important to perform change detection on the input data, either in hardware or software [41].

Reducing energy consumption of a specific hardware chips such as GPUs is already a key priority for hardware designers [42]. However, there is a need to understand their interaction with the rest of the system (server, battery) to decrease overall energy consumption.

In connection with CNN application based for HAR, it will be interesting to design new deep learning methods that fully exploit the distributed nature of the edge and to develop subsequent algorithms and software that will enable the deployment of hybrid edge/fog infrastructures. Future works will be around extensive tests to make out the system limitations in terms of power consumption, execution speed and memory utilization. These tests will be accompanied by the exploration of different HAR application.

IV. Conclusion

Based on the above survey, the following findings about DL architectures are summarized as follows:

- CNNs are able to extract features and perform classification, and they are faster in training than LSTMs. However, they present challenges related to sequence analysis due to the impact of data sparsity and irregularity (effect on understanding of context and long-term reasoning). Data sparsity also makes it more difficult to manage the variability of smart home data across its various parameters.
- The implementation of CNN parallel computing technique is a solution to reduce the learning and testing time [6], [8].

The major findings about hardware architectures are summarized below:

- Microcontrollers are often directly connected to sensors and actuators. This makes it possible to limit the latency of time. However, they are restricted in terms of calculation.
- Edge computing is characterized by autonomy. It allows reducing communication latency, traffic network, communication costs and problems of confidentiality. However, Edge devices are peripherals limited in resources and cannot take into account high computational loads. Also, storing data locally risks loss of data.

The new research directions and solutions around the study of main performance factors for DL on embedded equipment are summarized below to improve this field.

- Evaluate the database quality in real-time using the concept of spread rate whenever new training data is introduced. In fact, a good quality database means that its points are evenly distributed over the entire normalized feature subspace. For example, when all points are the same, the lowest quality is achieved, but what is the highest quality? The spreadrate score [11] could be used to measure how much the points of a normalized database regularly cover the space.
- Detect the ambiguous outliers in real time using deep auto-encoding model.
- Develop new algorithms for getting a minimal sensor setup to solve the issue of inability to install numerous sensors in smart building. A Principal Component Analysis (PCA) technique could be investigated for this purpose.
- Design new deep learning methods that fully exploit the distributed nature of the edge, and to develop subsequent algorithms and software that will enable the deployment of hybrid edge/fog infrastructures.

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