We Rock the Hizzle and Stuff

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***Abstract*—Future vehicular communication networks call for new solutions to support their capacity demands, by leveraging the potential of the millimeter-wave (mm-wave) spectrum. Mobility, in particular, poses severe challenges in their design, and as such shall be accounted for. A key question in mm-wave vehicular networks is how to optimize the trade-off between directive Data Transmission (DT) and directional Beam Training (BT), which enables it. In this paper, learning tools are investigated to optimize this trade-off. In the proposed scenario, a Base Station (BS) uses BT to establish a mm-wave directive link towards a Mobile User (MU) moving along a road. To control the BT/DT trade-off, a Partially Observable (PO) Markov Decision Process (MDP) is formulated, where the system state corresponds to the position of the MU within the road link. The goal is to maximize the number of bits delivered by the BS to the MU over the communication session, under a power constraint. The resulting optimal policies reveal that adaptive BT/DT procedures significantly outperform common-sense heuristic schemes, and that specific mobility features, such as user position estimates, can be effectively used to enhance the overall system performance and optimize the available system resources.**
This is a sample abstract, just to show as an abstract should be. It is 204 words long, I would say an abstract should not be longer than 250 words. Here, you should briefly state: 1) technical scenario and its importance, 2) what you do in the report / paper and why it is important, 3) if possible, summarize the main results. The abstract should be written in a way that motivates the reader to delve into the paper, but at the same time it should contain enough information to deliver the main message about the paper, so that the reader will now what can be found within the paper even without reading it (as it is the case most of the times). The abstract is a mini-paper on its own and, as such, is a major endeavor to write.

***Index Terms*—Mm-Wave, Vehicular Networks, Optimization, Beam Training, Data Transmission, Partially Observable MDP.**
A list of keywords defining the tools and the scenario. I would not go beyond *six* keywords.

I. Introduction

During the past decade, time series classification has captured growing interest thanks to the introduction of deep learning techniques, such as neural networks. These tools indeed are able to learn on their own the features of a signal, which are then exploited for classification, without the need of human domain-knowledge: this is a huge step forward considering that features were traditionally hand-crafted. [?] Human Activity Recognition (HAR) in particular has been fostered by the spread of powerful, efficient and affordable sensors, which nowadays are commonly found in mobile phones and wearable devices, with multiple applications, ranging from health care to gaming. [?] These on-body sensors allow us to collect and process a huge amount of signals, which is essential for deep neural networks to work properly: training data in fact is what they need, to learn and become accurate enough to be preferred over more traditional (machine learning) approaches. HAR anyway isn't an easy task: when dealing with on-body sensors, human behaviour can determine the performances of the systeml being it subject to high variability; moreover, data is typically high-dimensional, multi-modal and subjected to noise, making the problem even more difficult from a machine learning perspective.

In the recent years, several models to perform activity detection and classification have been proposed [?], but as pointed out in [?] and [?], the lack of a baseline evaluation setup and of implementation details prevented a fair comparison between them. To tackle this problem

In this paper we present our system to recognize human activity, tested on a benchmark dataset, the OPPORTUNITY Human Activity dataset [?]. Our model ...

Maximum length for the whole report is 9 pages. Abstract, introduction and related works should take max two pages.

A good way of structuring the introduction is as follows:

- one paragraph to introduce your work, describing the scenario *at large*, its relevance, to prepare the reader to what follows and convince her/him that the paper focuses on an important setup / problem.
- a second paragraph where you immediately delve into the specific problem that is still to be faced, starting to point the finger towards your contribution. Here, you describe the importance of such problem, providing examples (through references) of previous solutions attempts, and of why these failed *to provide a complete answer*. This second paragraph should not be too long, as otherwise the reader will get bored and will abandon your paper... It should be concisely written, something like 4 to 5 lines.
- a third paragraph were you state what you do in the paper, this should also be concisely written and to the point. A good rule of thumb is to make it max 10 lines. Here, you should state up front 1) the problem you solve, 2) its importance, 3) the technique you use, 4) stress the novelty of such technique / what you do. 5) comment on how your work / results can be reused / exploited to achieve further technical or practical goals.
- after this, you provide an itemized list to summarize the paper contributions: maximum six items, maximum four lines each.
- you finish up by reporting the paper structure, this should be three to four lines. It is customary to do so,

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Special thanks / acknowledgement go here.

although I admit it may be of little use.

Lately, I tend to write introduction plus abstract within a single page. This forces me to focus on the important messages that I want to deliver about the paper, leaving out all the blah blah. **Remember:** 1) *less is more*, 2) writing a compact (*snappy*) piece of technical text is much more difficult than writing with no space constraints.

II. Related Work

The OPPORTUNITY activity recognition dataset is a benchmarking dataset, introduced in [**?**], to overcome the lack of an evaluation setup to compare different classification systems and to provide a more exhaustive dataset compared to the others, which "are not sufficiently rich to investigate opportunistic activity recognition, where a high number of sensors is required on the body, in objects and in the environment, with a high number of activity instances". As pointed out in [**?**] in fact, previously, several datasets were related to the activities which were to be classified: this is due to researchers acquiring signals only from sensors located in specific locations, according to the task to be performed. The OPPORTUNITY activity recognition dataset instead has the purpose of collecting signals from an entire environment to enable a fair comparison of different learning models.

The goal of this section is to describe what has been done so far in *the* literature. You should focus on and briefly describe the work done in the best papers that you have read. For each you should comment on the paper's contribution, on the good and important findings of such paper and also, 1) on why these findings are not enough and 2) how these findings are improved upon / extended by the work that you do here. At the end of the section, you recap the main paper contributions (one or two, the most important ones) and how these extend / improve upon previous work. If possible, I would make this section no longer than one page, this leads to an overall *two pages* including abstract, introduction and related work. I believe this is a fair amount of space in most cases.

- **References:** please follow this *religiously*. It will help you a lot. Use *bibtex* as the tool to manage the bibliography. A bibtex example file, maned `biblio.bib` is also provided with this package.
- When referring to **conference / workshop papers**, I recommend to always include the following information: 1) author names, 2) paper title, 3) conference / workshop name, 4) conference / workshop address, 5) month, 6) year. Examples of this are: [**?**] [**?**].
- When referring to **journal papers**, include the following information: 1) author names, 2) paper title, 3) full journal name, 4) volume, 5) number, 6) month, 7) pages, 8) year. Examples of this are: [1] [2] [3].
- For **books**, include the following information: 1) author names, 2) book title, 3) editor and edition, 4) year.

Note that some of the above fields may not be shown when you compile the Latex file, but this depends on the bibliography settings (dictated by the specific Latex style that you load at the beginning of the document). You may decide to include additional pieces of information in a given bibliographic entry, but please, be consistent across all the entries, i.e., use the same fields. Exceptions are in the (rare) cases where some of the fields do not exist (e.g., the paper *number* or the *pages*).

III. Processing Pipeline

I would start the technical description with a *high level* introduction of your processing pipeline. Here you do not have to necessarily go into the technical details of every processing block, this will be done later as the paper develops. What I would like to see here is a description of the general approach, i.e., which processing blocks you used, how these were concatenated, etc. A diagram usually helps.

We start off our analysis by preprocessing the collected signals within the MATLAB framework: we chose that because it makes it simple to deal with matrices. What we do in this first step is then to import the data collected by sensors, which are given as .dat files, select the signals from on-body sensors and discard the others, replacing the missing values by means of interpolation and, at last, store them as .mat files. What we do next is to import the stored data, this time using python, and prepare the matrices for the classification task: this consists of concatenating the data, segmenting it into windows, scaling the signals and other common steps. Once the data is ready to be classified, a model is defined and trained on the available data. This is done for both the locomotion activity and gestures recognition, i.e. with two different sets of labels. This system, which is forced to learn also the null class together with the actual movements, is then compared to a different system where two models are deployed: the first one has the only purpose of detecting activity, while the second classifies the activity, if present.

IV. Signals and Features

Being a machine learning paper, I would put here a section describing the signals you have been working on. If possible, you should describe, in order, 1) the measurement setup, 2) how the signals were pre-processed (to remove noise, artifacts, fill gaps or represent them through a constant sampling rate, etc.). After this, you should describe how *feature vectors* were obtained from the pre-processed signals. If signals are *time series* this also implies stating the segmentation / windowing strategy that was adopted, to then describe how you obtained a feature vector for each time window. Also, if you also experiment with previous feature extraction approaches, you may want to list them as well, in addition to (and before) your own (possibly new) proposal.

The signals that we use to perform HAR are the ones collected in the OPPORTUNITY activity recognition dataset. The measurement setup is then the one presented in [**?**] and [**?**]. Our analysis though is based only on on-body sensor signals, which means that we kept the signals of only a subset of the available sensors: discarding the other signals then, we ended up with 113 signals. During the preprocessing, we discarded also 3 of them, belonging to the same physical device, because there weren't any measurements in most of the cases. This led us to work on 110 signals. Since we noticed that the almost all the sensors, at the beginning and at the end of the measurement sessions, have sequences where there isn't any sample recorded, we decided to discard the head and the tail of each session, in such a way that we start and stop with all the measurements being registered. This choice was made also to facilitate interpolation. In MATLAB we perform a splines interpolation, which uses a cubic polynomial. The decision of cutting head and tail prevented our code from interpolating a piece of signal which has only one "edge". Then, to perform classification on the data of one subject, we stacked sessions ADL 1 to 3 and Drill to create our training set, and then ADL4 and ADL5 as test set. In some cases, interpolation leaves entire columns to NaN because it isn't provided any data to interpolate those values. We solved the problem by setting to 0 those entire columns. Subsequently we scaled the signals by subtracting their means and dividing by their variance (or sigma?). After this, data is shaped into windows of 15 samples (500 ms) with a stride of 5 samples. The approach that we used to segment the data was then the sliding window introduced above. To perform classification, though we had to assign to each window a unique label, which we decided to be corresponding to the label present with more samples. This doesn't constitute a problem per se, even when changing the size of the sliding window, as long as it is kept short enough and ...

V. Learning Framework

Here you finally describe the learning strategy / algorithm that you conceived and used to solve the problem at stake. A good diagram to exemplify how learning is carried out is often very useful. In this section, you should describe the learning model, its parameters, any optimization over a given parameter

A. One Shot Classification

B. Two Steps Classification

VI. Results

In this section, you should provide the numerical results. You are free to decide the structure of this section. As general rules of thumb, use plots to describe your results, showing, e.g., precision, recall and F-measure as a function of the system (learning) parameters. Present the material in a progressive and logical manner, starting with simple things set, etc. You can organize this section in sub-sections. You are free to choose the most appropriate structure.

One of the main problems in Human Activity Recognition is handling inactivity.

Thinking of a real recognition system, In this paper we compare two different learning strategies, mimicking a real system. In the first V-A, One Shot Classification, the model is trained to learn a representation of the involved classes together with the null class

and adding details and explaining more complex behaviors as you go. Also, do not try to explain / show multiple concepts at a time. Try to address one concept at a time, explain it properly, move to the next one.
The best results are obtained by generating the graphs in either `encapsulated postscript (eps)` or `pdf` formats. To plot your figures, use the `includegraphics` command.

VII. Concluding Remarks

This section should take max half a page.

In many papers, here you find a summary of what done. It is basically an abstract where instead of using the present tense you use the past participle, as you refer to something that you have already developed in the previous sections. While I did it myself in the past, I now find it rather useless.

What I would like to see here is: 1) a very short summary of what done, 2) some (possibly) intelligent observations on the relevance and *applicability* of your algorithms / findings, 3) what is still missing, and can be done in the future to extend your work. The idea is that this section should be *useful* and not just a repetition of the abstract (just re-phrased and written using a different tense...).

Moreover: being a project report, I would also like to see a specific paragraph specifying: 1) what you have learned, and 2) any difficulties you may have encountered.

References

[1] C. E. Shannon, "A mathematical theory of communication," *The Bell System Technical Journal*, vol. 27, pp. 379–423, July 1948.
[2] S. Boyd, N. Parikh, E. Chu, and B. P. J. Eckstein, "Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers," *Foundations and Trends in Machine Learning*, vol. 3, pp. 1–122, Jan. 2011.
[3] D. Zordan, B. Martinez, I. Vilajosana, and M. Rossi, "On the Performance of Lossy Compression Schemes for Energy Constrained Sensor Networking," *ACM Transactions on Sensor Networks*, vol. 11, pp. 15:1–15:34, Aug. 2014.