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SMC2015 Cyber: Acceptance of Paper #9896 for Poster Presentation

SMC2015 Cyber <smc@ifs.tuwien.ac.at> 2015年6月11日 下午5:16
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Dear Ya-Hung Chen,

We are glad to inform you that your paper entitled "Monitoring Elder's Living Activity Using Ambient and Body Sensor Network in Smart Home" has been accepted for Poster presentation at the IEEE SMC 2015 Conference, part SMC2015 Cyber.

Comments from the reviewers are included with this message. Please consider their comments carefully when preparing the final version of your paper.

The following instructions will provide guidance about how to complete your accepted paper:

1- The maximum length is 6 pages, including figures and tables. Please note that SMC offers the option of having a maximum of 8 pages, with a charge of US$125 per page for pages 7 and 8.

2- No addition, deletion or change of the order of the author list is allowed.

3- Authors are requested to submit their papers and copyright forms electronically using the ConfDriver system (update the paper) at https://confdriver.ifs.tuwien.ac.at/smc2015/ on or before July 20, 2015 (HARD DEADLINE). The Registration system will be open on June 17, 2015. At least one of the authors listed in the paper must pre-register (either full or student registration) for the conference on or before July 15, 2015 in order to include the final camera-ready paper(s) in the conference proceedings.

4- Papers must be prepared using an IEEE SMC formatting template for papers http://www.smc2015.org/formatting).

5-You must attend the conference for your paper to be published in the proceedings. The SMC No-Show policy will be enforced. Please read it before you register (http://www.smc2015.org/registration).

6- If you need any assistance in the preparation of your camera-ready copy, please feel free to contact us via smc@ifs.tuwien.ac.at

7- Please do not hesitate to contact us via confdriver@ifs.tuwien.ac.at in case you have any technical difficulty with the ConfDriver system.

Thank you and congratulations on the acceptance of your contribution to SMC2015 Cyber.

Best regards,

Tin Kam Ho, Witold Pedrycz and Christopher Nemeth SMC 2015 Program Co-Chairs

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REVIEW 1

COMMENTS
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This is a good application paper where a practical case of combining two different signal types is described. The need

for combining data from several sources that are different by nature is currently seen in across different industries where data scientists work.

Hierarchical model is a natural solution, so that transformed data from one source compliments data form a different source.
In this paper researches transform continuous signal from a smart watch with tree-axial accelerometer. This signal source provides data in form of 3 features each representing mean and variance of acceleration in one of three dimension every 0.5 second. That is, initial processing of this continuous signal is some sort of discretization (you might consider other discretization approaches in the future). Smart watch in this case detects hand motion and body motion.

This design brings up many questions (I wish to see more details there), as one can imagine there are distinct patterns that can be detected with such signal, while majority of signals would be hard to assign to a meaningful pattern. For example, "the number of consecutive waving motions can be associated with one specific activity". There are many activities associated with consecutive waving motions. It would be great to recognize activities of interest for the problem at hand, label them, and disregard the others. It seems that is how it was designed with activities like reading, sleeping, etc. Yet the error rate must be high, and this signal needs deeper exploration, for example through clustering, visualization, time series (without transformation to mean and variance, possibly).
The cornerstone of this approach is to label these recognized patterns to learn a model from it, and these labels are of crucial importance as the error at this level will be transferred to a different level. It would be great to see more explanation why Dirichlet Process Mixture Model (DPMM) have been chosen for this and what were other candidate models to choose from.

In general, part that discussed particular technique choices and why their properties were important for the problem at hand is missing or is not convincing like in case of DPMM. For clustering technique choices the only argument provided is the number of clusters does not have to be pre-set. Overall, the theoretical part is not presented well, while the intro/application part is.

There is not much detail to what data looks like, just a general description. Some real example would be of help. It has to be stated more clearly what is the set of per-defined labels and whether they were used for both types of data, if not all, how many instances/activities were manually labeled with which data source, etc.

Paper needs major revision from the presentation standpoint for theoretical and experimental parts.

Language & grammar: There were a couple of phrases that need to be rewritten as it's hard to understand, 3rd page, paragraph 1:
"We statistic the occurrence time of each ..." "The temporal information is hardly extracting " "The training feature of 2nd-layer DPMM are grouped into one new feature by 60 continuous output of 1st-layer 2LDPMM."
3rd page, paragraph 3: "returns the probabilities of K rival events", meaning "mutually exclusive"?
page 4, top of the 2nd column: "There are existing the number of successes in a sequence of independent data that each data in one of k possible"

The rest of this section looks like it needs more language correction. Quite a few broken phrases.

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REVIEW 2

COMMENTS
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The authors propose a monitoring system for elderly's daily activity using home and body sensors. It is based on an unsupervised method of sensor input clustering based on the Dirchlet Process mixture model and X-means. Experimental results show that the unsupervised method produce activity recognition accuracy close to the supervised approaches.
- The paper is overall quite clearly written and the experiments well-performed. The main issue I found are some confusing sentences in the experimental results section. - Should the first mention of Table III in IV.B be Table II instead? Even then the text description does not match Table II completely. This part is rather confusing and the authors need to clean it up.