following the protocols guidelines. In our tests we incremented progressively the number of Gaussians (I) contained in every state and we reported the trend of the accuracy rate when incrementing I. For the first protocol we obtained the best results of 93.91% having $I = 31$. For the second protocol we obtained the best results of 74.2% when $I = 13$. The results are similar to those obtained when using GMMs.

The main advantage of this approach consists in the computation of the state sequence. Using the Viterbi alignment we recovered the most probable sequence of states (called *alignment*) that we compared with the data labelling. In the standard case the *alignment* is generated by the model recognised by the classifier and therefore it could be wrongly selected. Otherwise we can inject *a priori* the knowledge of the correct model. Depending on the case, we obtained two different results in terms of accuracy rate, respectively called AR_R and AR_{Or}. For the first protocol we obtained $AR_R = 93.5\%$ and $AR_{Or} = 93.6\%$ when $I = 31$. For the second protocol we obtained $AR_R = 90.4\%$ and $AR_{Or} = 91.4\%$ when $I = 13$. The appliance state recognition provided good accuracy rates even for the *unseen appliance* protocol that appears more challenging in the recognition of the appliance category.

We also realized a real-time application for the appliance and state recognition. This application has two main functions: data visualization and data classification. The data upcoming after the establishment of the connection can be visualized real-time after less than one minute, given the possibility to the user to select the feature and the dynamic components of his interest. The appliance and state recognition can also be performed providing the two classification results in real-time. We used the emission and transition matrices of all the models for the best case ($I = 31$) of the *Intersession* protocol. After less than one minute the classification results were available but given the small amount of time were not trustworthy. In our future works we plan to evaluate the system performances in classification task by using small data durations.

Information about the user activities can be extracted from the state transitions: we should be able to know when the user interacted with the appliance. We plan to use finer models with more states per category and eventually inject this information in systems used for the activity recognition in Smart Home / Buildings. Sensible improvement could be provided by merging the data used in this paper with other data coming from different datasets.

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