Personalized Eating Detection Using a Smartwatch

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Understanding the dietary habits of people plays a crucial role in interventions promoting healthy lifestyle. Obesity, which is a consequence of bad nutritional habits and increased energy intake, can be a major cause of cardiovascular diseases, diabetes or hypertension. Monitoring eating habits of overweight people is an important step towards improving nutritional habits and weight management. Another group of people that require monitoring of their eating behaviour are people with mild cognitive impairment and dementia. They often forget whether they have already eaten and, as a result, eat lunch or dinner multiple times a day or not at all, which might cause additional health problems. Proper treatment of these issues requires an objective measurement of the time at which the meal takes place, the duration of the meal and what the individual eats.

This work addresses a part of the technical challenges for a practical and reliable automated food intake monitoring system, specifically we focus on detecting eating activities. The main goal of our study is to develop a system that uses unobtrusive sensors that can be easily used during daily life activities. For this study we recorded data from 9 subjects in real-life scenarios, using a commercially available smartwatch containing 3-axis accelerometer and gyroscope. Each of the subjects had to record their activities including meals for at least two days, wearing the smartwatch on their dominant hand. Overall, the dataset contains 67 meals. There were no limitations about the type of activities that the subjects can perform during the day, nor the type of meals they can have.

The developed method relies on machine learning, following the established activity-recognition paradigm. It consists of three stages. The first two aim at training an eating detection models on an appropriate amount of representative eating and non-eating data. The first stage builds eating-detection models using all instances of eating and a subset of non-eating data (because there is much more non-eating data). The second stage adds some non-eating training data that is difficult to classify with the first-stage models. The third step takes into account the temporal information between predictions and smooths them using Hidden Markov Model. For this study, along the time-domain and frequency domain features, we developed some eating-specific features based on auto-correlation, which significantly improved the accuracy.

The experiments we performed showed that eating styles vary from person to person to a large degree. So, we decided to investigate the effect of personalized models. We evaluated the personalized models using leave-one-day-out cross-validation technique. In other words, in the training dataset for each subject we included data from all other subjects, and all days that the subject recorded except one, on which we later tested the performance of the trained model. The same procedure was repeated for each subject's day. For this study, we used the Random Forrest classifier, because it has been proven to be effective in the field of activity recognition. We analyzed the following evaluation metrics: recall, precision and F1 score. We achieved the precision of 0.7, recall of 0.85 and F1 score of 0.77. These results are calculated as a mean value from all subjects. The achieved precision and recall are encouraging for further work on this problem if we have in mind that the presented results are obtained on real-life recordings without any limitations on the subjects' daily activities.