Towards detection of chewing motion in the elderly using a glasses mounted accelerometer

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Abstract— **In this work, we propose the use of a glasses mounted accelerometer to detect chewing motion in the elderly. Data from 13 elderly was collected during their daily meals. This data is used to evaluate a k-Nearest Neighbor classifier.**

I. Food Intake monitoring

Nutrition plays an important role in both the physical and physiological health of an elderly person [1]. Preventing and curing malnutrition often starts with a self-monitoring process in a food diary or questionnaire. However, this method is time-consuming. We therefore suggest the use of technology to automatically detect food related Activities of Daily Living (ADL). To detect ADL related to food intake in a home environment, the use of unobtrusive and comfortable sensors is necessary. While camera, audio or strain gauge based systems perform well in a lab environment, these systems are difficult to adapt to a home environment as well as being not easy to use by the elderly [2]. Since many elderly already wear glasses on a daily basis, we suggest the use of a glasses mounted accelerometer. In previous work we have already shown that it is possible to automatically detect a person's chewing motion using an accelerometer mounted on a pair of glasses [2]. However, this work evaluated the technology on a small data set of young to middle aged subjects. The goal of this abstract is to evaluate the feasibility of this type of sensor for use in elderly adults.

II. Dataset

Data was collected in a care home from 13 elderly with a minimum age of 65. All subjects were able to independently consume their meals, but had a high daily care requirement. Measurements consist of each person consuming a single meal while wearing a pair of glasses with the accelerometer attached to the outside around the temple area. The accelerometer is a Shimmer3 unit sampling at 128Hz. Data was annotated between chewing and not-chewing using a video recording of the measurement. An epoch of chewing is considered to be the time between when a person first starts chewing a new bite and when the person swallows. The non-chewing label contains everything else during the meal, e.g.: talking, cutting, drinking, etc. A total of 93.8 minutes of chewing and 315.5 minutes of not-chewing was recorded.

III. Methodology

From the tri-axial accelerometer signal, we only use the signal mediolateral to the subject. We found that this axis contains the most useful information. The data is first filtered using a linear phase high pass filter with a cut-off at 0.5 Hz. For each person, the data is split in two signals, each signal containing only the chewing and non-chewing data. These signals are then segmented in windows of 15 seconds. The 25th and 75th percentile values of the frequency spectrum of each window are used as features. The features are then fed to a classifier on a per-window basis.

A k-Nearest Neighbor (KNN) classifier with k=3 is used to perform the classification. Because our dataset is unbalanced with an average ratio of 1 window of chewing per 3 windows of non-chewing, precision and recall are used as performance metrics. Validation is done using the leave-one-person-out method. Data of one person is used to evaluate a model that is built with the data of all other persons. This is done once for each subject in the dataset. Average precision and recall is calculated over all iterations.

A person-specific experiment is also performed, where for each person individually, the data of that person only is used to evaluate a KNN classifier using 10-fold cross validation.

IV. Results and discussion

Performing the leave-one-person-out validation for the entire dataset (13 times), resulting in a group-specific classifier, results in an average precision of 61.4 ± 22.7% and average recall of 56.0 ± 27.0%. Four out of 13 subjects had a precision of less than 40%, with the next highest performer at 66%. These same 4 subjects also perform badly in the person-specific experiment, with an average precision of 50%, while the average precision of the remaining subjects in the person-specific experiment is 79%. While the results of this experiment are biased, as data from the same person is used to train and test the classifier, the fact that the same 4 subjects perform subpar for both the group- and person-specific approach, as compared to the remaining subjects, indicates that our method does not work well for the entire dataset, but it is feasible for a large subset. Discarding the results of the 4 subjects, results in an acceptable average precision of 74.6 ± 10.5% and average recall of 62.1 ± 27.3%.

The primary reason for the low performance in these subjects is the fact that data was recorded in an uncontrolled environment. Subjects were allowed to interact with their neighbors at the table and with the researcher. The data therefore contains many epochs of miscellaneous activity such as talking. Using our simple set of features, it proves difficult to distinguish the chewing motion from the miscellaneous activities. Future work regarding feature selection and classification is required to obtain a classifier that performs well enough for the entire dataset in a real-world environment.

References

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