Algorithmic Detection of Pediatric Chewing Sequences Using the Automatic Ingestion Monitor (AIM)

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Introduction: The current clinical standard for measuring chewing ability is the "Test of Masticating and Swallowing Solids (TOMASS)." The TOMASS relies on clinician ratings of number of bites, chews, masticatory cycles, and measurement of the time needed to ingest a cracker. Clinicians need an objective test of chewing ability to accurately diagnose and treat pediatric feeding disorder. The Automatic Ingestion Monitor (AIM) sensor system has the potential to provide a completely objective assessment of chewing skills in children.

Materials and Methods: The jaw sensor of the AIM sensor system was put on seventeen pediatric participants who were instructed to take at least five bites of a puree (pudding or apple sauce), meltable solid (graham crackers), cubed solid (cubed ham or a fruit cup), soft material (muffins), and hard material (fruit leather or a CLIF bar). The strain response of the jaw sensors was collected, filtered to signals between 0.5 Hz – 2.5 Hz, and segmented into portions where each food type was eaten.

The two methods described classified chews by counting the peaks above a certain strain response (y-value) as chews. Our benchmark method to detect chews used a value of strain response that minimized the error percentage of each group, a standardized value that determine if a peak is considered a chew or not. The method that best reduced the error of used a standardized percentage of the average of the absolute value of each chewing signal.

Results: The average error percentage rate was computed for each method and portion of the procedure on data provided by the entire group. A two-sample t test ($\mu < \mu_0$, $p < 0.05$) was conducted, comparing each mean and standard deviation to the mean and standard deviations of our benchmark method.

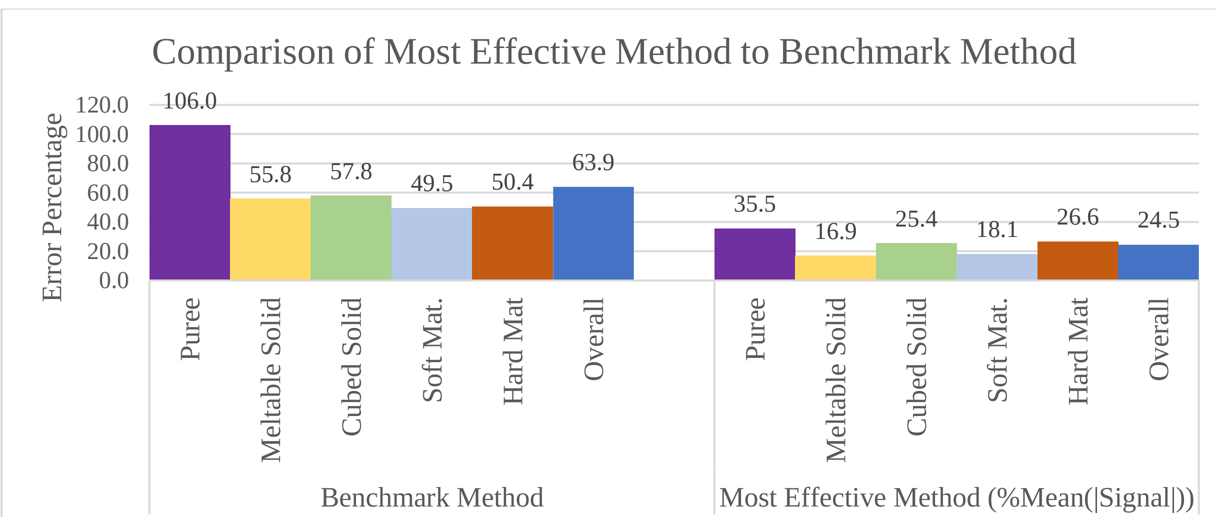

Figure 1. A chart comparing the error percentages for each method.

Conclusion and Further Direction: The comparison of our best performing method was found to confirm our alternative hypothesis for each portion of the test (puree (p = 0.031), meltable solid (p=0.005), cubed solid (p=0.015), soft material (p=0.004), hard material (p=0.035), overall (p=0.015)). Using our best method, we were able to drive the overall chewing detection error down from 63.9% to 24.5%.

In addition to this peak detection algorithm, a classifier trained on this data set will be able to drive down the error percentages to an acceptable level. A video classification algorithm that determines bites and chews from a recording of the procedure is being refined to detect bites and chews in a pediatric population. Finally, we hope to use the next version of the AIM sensor system to detect chews.