Exploring Kinect Sensor readings of body postures as an indicator of student frustration levels in makerspaces

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Abstract
This paper explores the feasibility of an automated system that estimates learner frustration levels through analyzing body postures; captured through Kinect sensors. Using body posture data collected in a makerspace on a class of 16 students throughout a semester, and combining that with weekly survey results in which students self-reported their frustration levels -among other affective, cognitive and social aspects- this paper takes exploratory steps to test the ability of kinect data to estimate student frustration. The ultimate goal that this paper contributes to is the creation of a sensor based system that supports learning in low-scaffold environments such as makerspaces by reporting reliable measures of student affective states.

Keywords
Kinect Sensors, Makerspaces, Body Tracking, Motion Capture, Learning Analytics, Student Frustration, K-means Clustering, DBScan

1. Introduction and motivation:

Makerspaces offer a characteristic Papertian constructionist setting for learners to explore building novel creations. In this learning environment, students engage with closer to real-world problems than in a classroom environment, and they practice their sense of determination and creative problem solving (Kurti, Kurti & Fleming, 2014). Undoubtedly, as makers work towards their objectives, this setting will elicit several affective states, including engagement, collaboration, enjoyment, and frustration. This paper focuses on and investigates the state of frustration as reported by students taking a class in a makerspace. The body postures of students are examined in contrast to their reported level of frustration with the aim of uncovering good indicators of frustration from body postures.

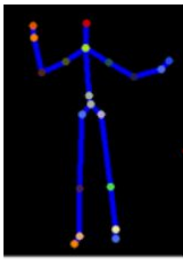
Teachers often struggle to figure out the affective states of their students. This information is important for the teacher to adjust her/his instruction approach to meet the learner where s/he is. However, such information is not easy to diagnose and track in a typical classroom environment. It is unreasonable to assume that a teacher will be able to pay attention to all students in the class all the time and be able to tell who is engaged, frustrated, joyful, bored, daydreaming, anxious etc. in addition to track changes in these affective states.

While some tools do exist (e.g. BrainCo Focus-1 headband and Empatica E4) and can be used to provide the teacher with such real time feedback; these devices rely on very few measures and are wearable. That a learner must have these on their body might in itself cause distraction and/discomfort. Also, in more active learning settings, wearables can move on the surface of the user's skin, which further threatens the quality of data collected.

It would therefore be great to develop a non-wearable tool that assesses affective states using several inputs. This can be thought of as a 6th sense that provides such information to the teacher in real time without requiring much of the teacher's attention and without influencing the learner.

This paper considers using Kinect sensors to accomplish this task.

The Kinect picks up body joint positions in 3D space of up to 8 skeletons at a time.



Can we diagnose learner frustration from their body posture clusters? This paper builds on the work of (Ramirez, Yao, Chng, & Schneider, 2019) in an attempt to answer this question.

2. Relevant Work:

Makerspaces are the possibly the closest settings modern teaching institutions have to offer that is close to Freirian situated learning; a concept that makes much pedagogical sense, but that has traditionally been seen as utopian (Blikstein, 2008). Despite their preeminence since the makerspace movement in the mid 00's, most makerspace studies have traditionally been qualitative; using observations or surveys. However, there seems to be a disproportionate availability of quantitative data about learners inside these places. Several viewpoints have emerged to address how makerspaces promote learning; at a high-level, some view the maker mindset as driven by self-expression (Benjes-Small et al, 2017), while others view it as driven by learner interaction with objects they create (Clapp et al, 2016). At any point on that spectrum, it is reasonable to claim that without reliable measures to gauge learning at such an open-ended environment, it is difficult for the teacher to coach the learner in a way that maximizes learning potential.

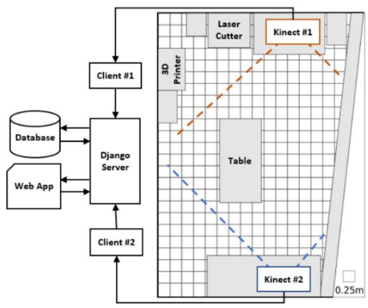
While frustration may be picked up using facial expression recognition (Kapoor & Pickard, 2005) with relative ease in learning environments where students change positions less frequently, in makerspaces, this is particularly challenging; students move around and interact with each others frequently, and their faces and body positional seldom remain unchanged. Further, students undergo affective state shifts that come in changing patterns, and frustration might depend on where a student is with their project - among other factors (Blikstein, 2013).

Some high accuracy models relying on external devices do exist (Behoora & Tucker, 2014; Aleven & Mostow, 2010), but they have severe limitations when is comes to open-ended environments where much movement happens. This makes it difficult for such facial expression recognition solutions (including those offered by Affectiva, etc.) to be viable solutions. In a similar fashion, wearable devices that are accurate in low-movement settings may restrict learner movements and affect the way they would naturally interact when applied in the high-movement environment. As such, instrumenting an external system that tracks learner affective states at an accuracy level comparable to that of more invasive devices would be ideal, and would dominate existing approaches.

Using the same data analyzed in this study, preliminary findings from (Ramirez, Yao, Chung & Schneider, 2019) suggests that estimating student levels of challenge and collaboration is feasible using Kinect sensors. In a similar fashion, this study attempts to explore the feasibility of using a Kinect based monitoring system to measure frustration.

3. Overview:

We use Kinect sensor data accumulated over a semester (13 weeks) of a class of 16 students as they use a makerspace (see figure below for exact room layout and Kinect sensor positions). Weekly surveys of student self-reported measures of frustration -among other affective states- are also used, and aim to serve as ground truth.

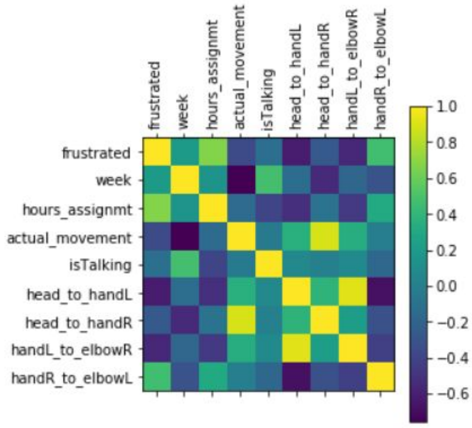


Research Question: is there a correlation between body posture clusters, conveyed through hand and elbow positions, and student self reported frustration levels?

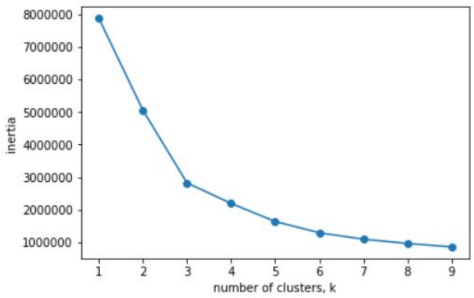
In a deviation from prototypical gestures (hands behind head, and hands behind back) surmised to indicate frustration as in (Behoora & Tucker, 2014), this research question intimates at the author's belief that a crossed arms position might have a higher correlation to frustration.

4. Analysis:

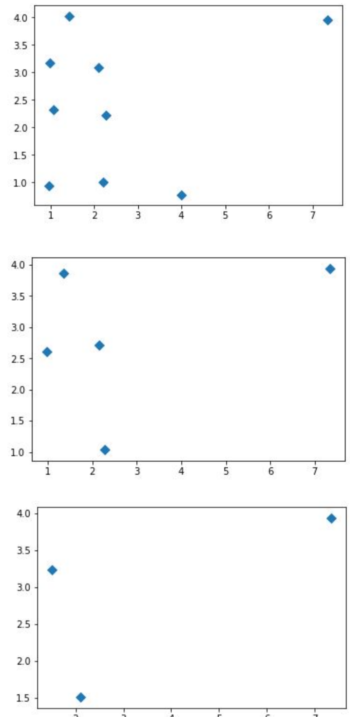
The first step was exploratory data analysis. The student self reports were aggregated by weekly average over all 16 students. Correlation matrices were then produced to examine the individual body positions on frustration (see figure below).



After that, the metrics of interest were subsetted, from the weekly raw kinect data, to include only the body positions of interest - namely, elbow and hand x,y positions. The resulting data frame consisted of over 780,000 observations and 8 columns ready for clustering. Several approaches were considered; hierarchical clustering and t-SNE were excluded from consideration because of large number of observations. K-means was retained as more reasonable approaches to the data due to control over model parameters. A scree-plot was then used to help inform the number of clusters for k-means. A Clear elbow was determined at 3 clusters (see figure below).



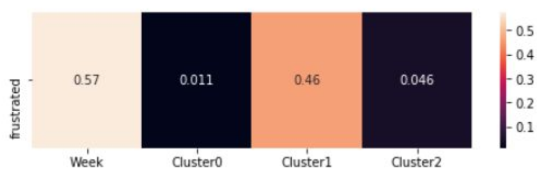
For further exploration, 9, 5, and 3 clusters were plotted side by side to visually inspect centroids. It appeared that 3 clusters provided a reasonable distance, while the additional clusters in 5 and 9 plots did not add much more distance to warrant use.



After that, a data-frame was created combining frustration per week with the number of times each cluster appeared in any given week. A correlation was then ran on the data (output is in the table and figure below).

Pearson's correlation	Week	Cluster 0	Cluster 1	Cluster 2
Frustration	0.2	0.76	0.26	-0.64

The p-values are reported below, and show statistical significance for cluster0 at $P \leq 0.05$.



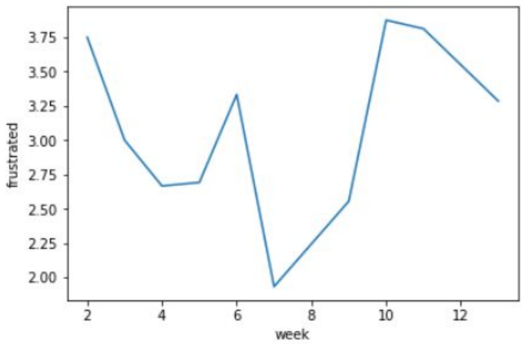
5. Results:

From the EDA, it wasn't surprising to see that head-to-hand distances were inversely correlated with frustration. It was interesting to see that cluster-2 exclusively appears in week 7; which is a concern that some error might have occured in the data cleaning section. This cluster appears to be the one in the top right corner of centroid plots above, and warrants further investigation.

Another interesting observation is that cluster-0 is significantly positively correlated with student reported levels of frustration at the 95% confidence interval. This may indicate that a certain distance between the hands and elbows can be used to predict the state of frustration; however further analysis is required to identify how this posture looks like, and whether it is valid at similar settings.

6. Conclusion:

This analysis aimed at investigating the correlation of frustration levels with the body postures as indicated by hand and elbow positions of 16 students in a makerspace over the span of 13 weeks. After using K-means clustering then counting the number of instances (over 780,000) associated with each cluster for each week, it seems that one cluster is significantly positively associated to higher reported levels of frustration. Despite calculating the correlation over only 13 weeks, the fluctuation in frustration by week (see figure below) is high enough to reduce the possibility of a spurious correlation taking place.



This, however, does not mean that cluster0 is the answer we are looking for. Further analysis is required to ascertain this cluster's role in predicting frustration.

7: Future Work:

It would be interesting to apply the same approach used here to more body posture combinations. For example, combinations of body postures, gaze direction (time facing equipment / time facing others) and speech quantity might be interesting measures. It would also be interesting to complete the analysis on a more granular basis (e.g. by day). Lastly, incorporating student-specific traits (e.g. making experience, personality type, demographics) as in (Behoora & Tucker, 2014) might be useful.

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