Review: Using Microsoft Kinect to Monitor Patients in the Home

Steve Sroba ssroba@andrew.cmu.edu
Heinz College
Carnegie Mellon University
Pittsburgh, PA, United States

1. Paper Review

1.1 Constructive Feedback

The problem was well posed, with a good introduction so that the reader can understand where this fits into health care, and how it could improve the quality of care while reducing costs. I could have narrowed it down to make it more clear, and also to get better results. Since the initial problem was very broad, I had to make decisions to focus my work later in the process. The most relevant works were cited, although there were many more I could have cited. Specifically, the most relevant, which is where I got the data set from, was well cited. The methods were clearly described in the background, model description, and experimental setup sections, with pseudocode examples to give the reader a better understanding. I think people with knowledge of Matlab could reproduce this, although they would not have access to the data set without sending a request to the owner. More advanced features could have been trained (such as windowed features rather than features that describe the entire record) and more classifiers could have been tested.

1.2 Summary

The hypothesis was that different exercises and people of different fitness levels performing these exercises can be classified from raw Kinect data. The results were 75.84% accuracy for classifying exercises, and 93.26% accuracy for classifying groups of participants.

1.3 Strengths and Weaknesses

The strengths of the paper are the background and application, and the explanation of the methods used. The weaknesses are the limitations of the data set, the fact that there is unbalanced distribution of groups of participants, lack of advanced features, lack of comparison between different types of classification algorithms, and the fact that the data set is private, so this is not reproducible without simulated code. This is similar to many studies, however, it is not common in current health care plans. The novelty comes in the large number of features used to train the ensembles, and the Bayesian Optimization used for tuning the hyperparameters, as well as the embedded method of feature selection. Figures, graphs, and tables were used extensively where appropriate. However, I had trouble formatting a few, so decided to leave them out since the paper was already long. The interpretations of

the study match the findings well, although I may have looked over the unbalanced groups of participants, and how that may have effected classification accuracy.

1.4 Next Steps

This type of home-based care that eliminates doctor visits, tracks patients, and classifies fitness level could be very common, and very important in the future of health care. With more time, I would have done more with feature extracting/engineering, tested other classifiers, analyzed phases of exercises rather than the exercise as a whole, and built a scoring mechanism to give patients a score based on the scoring methods used in the clinical tests that the exercises are based off of.

2. Code Review

The code is findable and accessible on Github, although it may take some searching to find it without the Github link. It uses Matlab toolboxes heavily, so it is not very interoperable with other coding languages and frameworks. With a license to Matlab and the toolboxes used in this study, as well as permission/access to the data set, the code is re-usable.

There are instructions for the code in the README file on Github, although there are no troubleshooting steps included. Comments throughout the code help understand what chunks of code are doing, although line-by-line comments would help give a better understanding.

It is hard to test/verify the results because the data set is private. A simulated data set would help with this. This could be made by generating fake patients that have the same distribution of demographics and fitness levels as the real data set, and generating fake Kinect records, where for each exercise, the distribution of X/Y/Z coordinates for each joint is the same as the real data.