

Dynamical Models for Instruction Completion and Error Recognition for NASA Physical Procedures

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Abstract

1. Introduction

Procedures are the accepted means to operate a spacecraft system or systems to perform specific functions, and consequently are at the heart of all NASA human space-flight operations [6]. A procedure is a detailed set of instructions specifying how a piece of equipment is operated or a task is performed [4]. They are often written to be very general and to cover numerous contingencies. Procedures to operate a class of equipment (e.g., smoke detector) will differ based on make, while procedures to operate a piece of equipment will have conditional or optional steps based on configuration. As an additional complication, constraints of some procedures may be highly conditional, discretionary, or unordered. At the same time, there may be external constraints that limit how a procedure must be executed, and these constraints are not made explicit. The outcomes of NASA missions rely on crew members properly executing a multitude of these complex procedures, making procedure execution support and monitoring a critical factor that can determine success or failure measured both in terms of monetary costs as well as preventing loss of life.

There is a body of prior NASA work focused on monitoring the progress of procedures that are not physical. For instance, when instructions to systems of the ISS are sent from ground, the application ThinLayer highlights commands as they are executed to show procedure progress [4]. IPV itself also allows for manually tracking procedure progress for a crew person onboard ISS. However, to date there is little work from NASA in the realm of tracking ex-

ecution status of physical procedures where crew members are manually manipulating physical objects, such as during maintenance tasks. Our goal with this work is to develop a method to computationally model a procedure to enable tracking of the execution of its steps and detection of crew errors during physical execution.

2. Related Work

Significant work has been done in the field of human action and activity recognition. Turaga et al. [9] presents a comprehensive overview of this work in detail. In most work, activity recognition is identified as the sum of *actions* performed in a temporal ordering. Parametric models, particularly Hidden Markov Models, have been used with success in many action recognition applications. Yamato et al. [10] employ them to identify whole-body tennis swings. Using background subtraction, they are able to identify the actor in the scene, and learn a model based on how the actor alone is moving over time.

The particular advantage of HMMs in the field of vision lies in their efficiency in modeling time-sequential data. Because the underlying representation of an HMM essentially encodes a state machine, they lend themselves nicely to modeling actions. Actions are composed of sequential time-varying video frames, and the model creates a representation with “probabilistic jumps” from one state to another. [9].

There has been some work in developing HMM formalisms that incorporate domain knowledge as well. Moore et al. [7] created a framework combining both HMMs and object detection modules to extract interaction information HMMs alone could not identify. Chen et al. [1], HMMs are used in conjunction with specific feature extraction methods

to recognize hand gestures.

While the above works have been significantly expanded upon, all of that effort has been under the assumption of a third-person view of the action, where the camera is removed from the scene. In our setup, our observation of the underlying scene occurs from an egocentric viewpoint. Egocentric cameras present their own unique affordances, and come with their own unique problems. Technological advances have only recently begun to make common use of egocentric cameras a reality, and as such there is a limited existing body of work to use as a foundation.

Though this does prove to be an interesting challenge, the task of instruction completion and error recognition provides us with significant domain knowledge. Rather than having a classification problem in which an unknown task is to be identified, we have significant knowledge of what has already been completed, what the correct next action should look like, and what error states look like. It is this knowledge that we hope to incorporate into our model.

In this way, we employ the concept of *activity* recognition, coupled with our action recognition. We model the entire activity as a set of actions completed in a specific order. To this end, Petri Nets [8] appear to apply quite well. The graphical model format, along with the unique properties of sequencing, concurrency, synchronization, and resource sharing[2] that Petri Nets provide allow for a complete high-level representation of the activity. Incorporating the entire procedure in the form of a Petri Net, coupled with the lower-level HMM, we hope to create a system which will allow for effective instruction completion and error recognition.

3. Feature-Action-Activity Pipeline

Because of our novel combination of a variety of vision and machine learning methods, a pipeline was developed to afford fast and efficient processing of raw video data directly through to the learning process.

3.1. Feature Representation

optical flow lucas kanade histograms (HOOF) RONAK

3.2. Codebook Generation

kmeans on HOOF RONAK

3.3. Hidden Markov Models

JOHN

3.4. Petri Network

-simulation JOHN

4. Experimental Evaluation

We evaluated our proposed TODO pipeline in a number of experiments. Below we describe our dataset, which was



Figure 1. The piece of exercise equipment and tools we used in the task to create our dataset.

constructed based off of an actual NASA procedure and related constraints. Additionally, we describe the acquisition of the dataset following by the results of classification experiments with and without use of the Petri Network.

4.1. Dataset

Frank et al. [5] describe several physical procedures frequently conducted on the International Space Station (ISS). One of these procedures is the Interim Resistive Exercise Device (iRED) Inspection and Cleaning task. This procedure involves crew disassembling the piece of exercise equipment, inspecting and cleaning the inner parts, capturing and sending inspection photos to ground control, and then reassembling the device. We based the task we created on this procedure.

The piece of exercise equipment we used for our task is shown on the left in Figure 1 with the necessary tools shown on the right. The complete disassembly, photographing, and reassembly task consists of 66 actions. However, we used only the first eight actions of the disassembly portion of the task in our dataset. This task therefore consisted of 1) removing an electronic display, 2 and 3) removing two resistance cords, 4) attaching the proper drill bit to an electronic screwdriver, 5 and 6) removing the two steps, 7) unscrewing by hand a resistance knob, and 8) detaching a wheel. This task involves a mixture of tool use and hand manipulation of components of a variety of parts on the exercise device. It therefore requires a large amount of participant mobility.

For the data collection, each participant executed the disassembly procedure with the instructions for the procedure delivered via a prototype task support system developed on the Google Glass¹ Platform, a lightweight head-mounted display device. These types of task guidance systems are being developed in other work, but this system provides a good platform for the acquisition of egocentric video information captured from the Glass device's camera, so it was selected for this purpose. The device was modified slightly

¹http://en.wikipedia.org/wiki/Google_Glass

to better capture the salient visual content of the task execution. The modified device is shown in Figure 2. We attached a mirror at an angle of approximately 25° from level to the device with a 3D printed mount. When manipulating objects with the hands in front of themselves, most people both tilt their heads downward slightly and look downward with their eyes. The head-mounted camera will move with the head tilt, and the mirror helps to correct for the additional downward direction contributed by eye movements. A sample frame captured from the egocentric camera and mirror during the task is shown in Figure ??.

Each of the authors executed the eight actions of the exercise procedure ten times, resulting in our dataset of 30 egocentric videos of the same task. The authors had varying degrees of prior knowledge of the procedure, so the data consists of procedure executors of multiple levels of skill, resulting in a variety of techniques and times needed to execute the procedure. For example, one author had no knowledge of the procedure, and therefore initially relied completely on the task guidance delivered by the Glass device to preform the procedure. By the end of his tenth execution, he had internalized the procedure, eliminating the need for the assistance device, and was significantly faster than before. His set of ten videos, therefore, has him performing at a continuum of expertise levels as he increased in familiarity with the procedure. Thus, while there were only three participants included in the dataset, we believe there is still ample variety in the dataset and that testing with this data will generalize to other executors of the same procedure. Each of the actions in the video was segmented by hand to use for training and testing purposes in the classification.



Figure 2. The modified Google Glass device we used to capture the video for our dataset. The attached mirror helps to capture manipulations of objects directly in front of the procedure executor.

4.2. Results

We evaluated our pipeline in a number of experiments using our exercise equipment disassembly dataset. In the following paragraphs we discuss the methodology used in our grid search of the pipeline parameters and the resulting accuracies.

We performed a grid search manipulating the following parameters: 1) the number of bins used in the HOOF histogram binning, 2) the size of the codebook of HOOF features, and 3) the number of states in the HMMs. To evaluate each parameter configuration, we used a leave-one-out cross validation technique where 29 of the 30 videos were used to generate the codebook and train the HMMs. The actions of the last video were then each passed through the pipeline and the predicted action was the one which had the highest probability from the set of HMMs. The results using the Petri Network of the task used a weighting factor of 0.98. In all cases, random number generation was seeded such that k-means and the HMMs will produce repeatable results. Additionally, both of these processes were run with enough iterations to ensure convergence. To evaluate the accuracies of predicting each action for each configuration, we averaged (by action) these 30 accuracy results to determine a configuration accuracy. The results for some of the parameter configurations are shown in Table ??.

While these accuracies are not spectacular, they are still significant in that random chance would put the accuracy at 0.125. Additionally, these results are comparable to accuracies in prior work that also use an egocentric camera [?]. In the next section we discuss the challenges we discovered with our technique and the implications for future methods to improve the results of real-time prediction of actions from egocentric cameras.

5. Discussion and Future Work

feature representation problematic -flow not good for egocentric -other work has used object detection -time limitation prevented us from training detectors and creating the training data -future work RONAK Fathi et al. [3] have camera encoding more scene information

6. Conclusion

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