Learning from Demonstration using GMM, CHMM, DHMM: A Comparison

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Abstract

Greater production and improved safety in the mining industry can be enhanced by the use of automated vehicles. This paper presents results in applying Learning from Demonstration (LfD) to a laboratory semi-automated mine inspection robot following a path through a simulated mine. Three methods, Gaussian Mixture Model (GMM), Continuous Hidden Markov Model (CHMM), and Discrete Hidden Markov Model (DHMM) were used to implement the LfD and a comparison of the implementation results is presented. The results from the different models were then used to implement a novel, optimised path decomposition technique that may be suitable for possible robot use within an underground mine.
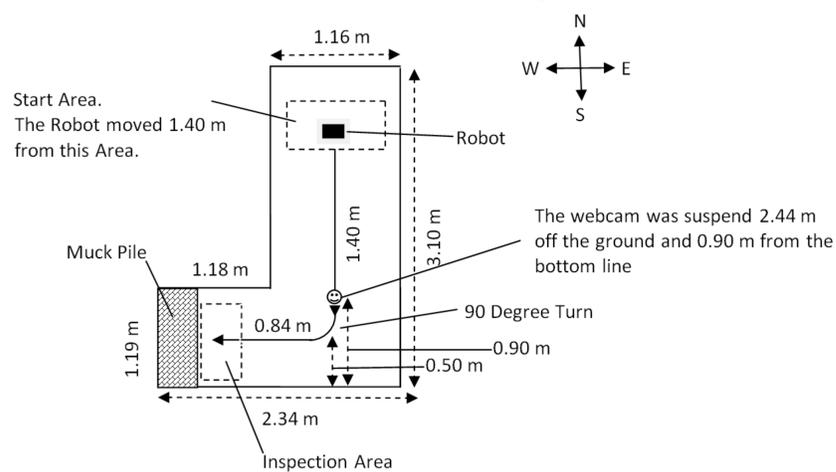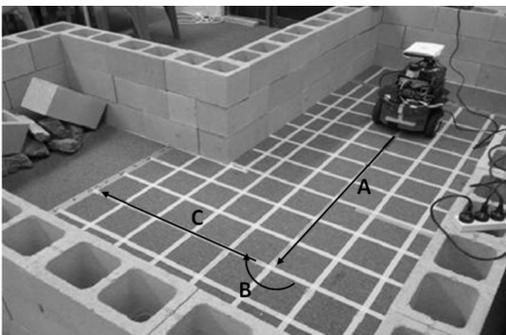
Fig. 1. Floorplan of the training environment.

Fig. 2. Original robot training environment with smooth walls

Fig. 3. Randomly placed obstacles (round tubes) to simulate a noisy environment.

Experimental Setup

Fig 1 shows the floorplan of the training environment. The concrete simulated mine tunnel shown in Fig 3 and Fig 4 was designed to reflect a more realistic environment for the robot. This was achieved by moving some of the concrete blocks in such a way as to make a very uneven wall contour. This allowed the full potential of LfD to be used in learning to traverse a very uneven, irregular environment. A P3-DX robot was used for experiments, and a webcam was used to capture the robot motion. A teleoperated robot was allowed to run through the training environment as shown in Fig 3. The robot acquired data from its on-board sonar sensors while traversing segment A, segment B and segment C. These segments were labelled A, B and C in Fig 3. It can be seen that segment A was a straight line from the starting position to a point at B where the robot needed to turn to the right. Segment B was the rotation through 90 degrees to face the simulated muck pile which was the desired end position for the robot. After turning, the robot then traversed segment C to end up facing the muck pile.

Experimental Results and Conclusions

For Segment A and C, the following performances were used and are displayed in Fig 4 and Fig 6.
1. Average Distance Error (ADE) which is an average of 10 DEs.
2. Time Error Ratio (TER) which shows time error between an average running time and the corresponding training time.
3. Fail Rates which show the number of failures for a learning kernel (e.g, wall strike).

For Segment B, Rotation Error Ratio (RER) is the performance showing degree error between an average stop spot and the ending point in training.

As shown in Figures 4 - 6, a variable has different variations on a section based on different methods and situations. For the purpose of comparing values of these variables, the values were graphed on the same scale. All variables with FR equal to 1 were assigned the maximum value in a corresponding scale. ADE was assigned to 60 and TER was assigned to 1.5 for any training with FR equal to 1 in Fig 4. RER was assigned to 2.5 and TER was assigned to 2 for any training with FR equal to 1 in Fig 5. ADE was assigned to 40 and TER was assigned to 1.5 for any training with FR equal to 1 in Fig 6.

The GMM based method had the best performance in a low noise environment. In practice, there's always unexpected noise around a robot, implying the GMM based method was not practical for real environments. The CHMM based method was suitable for turning trajectories, while The DHMM based method was more robust for straight trajectories.
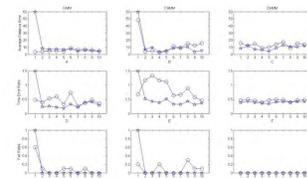

Fig. 4. Performance Comparison for Segment A under both environments. The circles represent performance in a low noise environment. The stars represent performance in a noisy environment. X-axes represent training numbers.
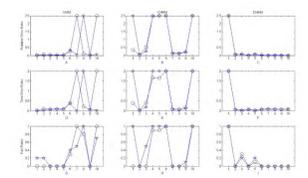

Fig. 5. Performance Comparison for Segment B under both environments. The circles represent performance in a low noise environment. The stars represent performance in a noisy environment. X-axes represent training numbers.
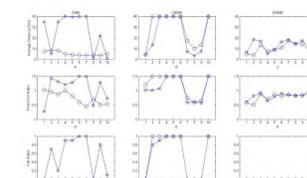

Fig. 6. Performance Comparison for Segment C under both environments. The circles represent performance in a low noise environment. The stars represent performance in a noisy environment. X-axes represent training numbers.

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