Deep Learning with Predictive Control for Human Motion Tracking

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Abstract - We propose to combine model predictive control with deep learning for the task of accurate human motion tracking with a robot. We design the MPC to allow switching between the learned and a conservative prediction. We also explored online learning with a DyBM model. We applied this method to human handwriting motion tracking with a UR-5 robot. The results show that the framework significantly improves tracking performance.

1. Introduction

Accurate control for human motion tracking is a key requirement in many applications including human-robot interaction, teleoperation systems, exoskeletons and surveillance systems. For these applications, better motion prediction models enable better control. But as the system complexity increases, conventional methods which require handcrafted models also become increasingly challenging to design. Deep learning architectures can provide this model given enough data.

Using deep neural networks end-to-end for difficult robot manipulation tasks was proposed in [1] but it is too data-inefficient. Contrary to this, several recent approaches have used a Model Predictive Control (MPC) framework such that deep learning is used only in the part which is difficult to model. For example, [2] learns complex contact dynamics for robotic food-cutting. In [3], the mapping of actions to image pixel motion is learned for vision-based manipulation tasks. In [4], a model is learned for predicting forces in a robot-assisted dressing task. In [5], the dynamics of aggressive driving is learned for controlling an autonomous car.

This work is in the same area of research where neural networks learn complex predictive models for use within an MPC framework. Specifically, we are learning models to predict human motion. As the representative task, the robot here has to write characters as a human, as shown in Fig. 1. We chose this task to leverage existing datasets on character writing such as [6]. In addition to being a new application area, we also design the MPC to be able to switch to a more conservative prediction. Furthermore, we also explore online learning using the Dynamic Boltzmann Machine [7] neural network.

2. Model predictive control framework for tracking control

A general MPC formulation can be expressed as:

\[ \hat{\mathbf{u}} = \arg \min J(\mathbf{x}_0, \hat{\mathbf{u}}) \]

subject to \( \mathbf{x}_{i+1} = f(\mathbf{x}_i, \mathbf{u}_i) \),

where the resulting sequence of future control actions, \( \hat{\mathbf{u}} = [\mathbf{u}_0 \ldots \mathbf{u}_N] \) is obtained by optimizing the objective function, \( J(\cdot) \), under the constraint of the system dynamics equation where \( \mathbf{x}_{i+1} \) is the resulting next state when the action, \( \mathbf{u}_i \) is applied while in state \( \mathbf{x}_i \).

The functions \( J(\cdot) \) and/or \( f(\cdot) \) can be fully or partially replaced by neural network models. This design choice leads to several different approaches. Here, we are using a neural network only as a part of \( J(\cdot) \) and design it such that the neural network is a model to predict the future human motion.

For \( f(\cdot) \), we assume that we can freely control the end-effector and that the motion is smooth so that the trajectory is differentiable three times. Doing so, we can define the end-effector state as the Cartesian position, velocity and acceleration. We then use the jerk for control. For a single time step, \( \Delta t \) and a single degree of freedom (DOF), the equation for \( f(\cdot) \) is linear such that: \( \mathbf{x}_{i+1} = \mathbf{A} \mathbf{x}_i + \mathbf{B} \mathbf{u}_i \), where:

\[ \mathbf{x} = \begin{bmatrix} c \\ \dot{c} \\ \ddot{c} \end{bmatrix}, \mathbf{u} = [c], \mathbf{A} = \begin{bmatrix} 1 & \Delta t & \frac{\Delta t^2}{2} \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} \frac{\Delta t^3}{6} \\ \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \]
We can apply the same model independently for the three translations. To obtain a vector of future states, \( \tilde{x} = [x_0 \ldots x_N] \), we can recursively apply \( f(\cdot) \) to get an arbitrarily long sequence of \( N \) future states. Doing so, \( \tilde{x} \) has length \( 9N \) (position, velocity, acceleration for 3DOF and \( N \) timesteps) while \( \tilde{u} \) is a column vector, with length \( 3N \) (jerk for 3DOF and \( N \) timesteps). A linear model for \( f(\cdot) \) can still be written such that: 
\[
\tilde{x} = \tilde{A} \tilde{x}_0 + \tilde{B} \tilde{u}
\]
where \( \tilde{x}_0 \) is the initial state. The matrices \( \tilde{A}, \tilde{B} \) are made from \( A, B \) through a process known in MPC literature as condensing.

For the objective function, we need to track the motion of the character being written. This can be done by minimizing \( \| \tilde{x}_{\text{target}} - \tilde{x} \| \) the L2-norm of the state to a target state, \( \tilde{x}_{\text{target}} \) requires future information so we need a predictive model. Here, we propose switching between two models: a conservative model, \( \tilde{x}_c \), which predicts no motion: just copying the last position with zero velocities and acceleration. This simple model has significant tracking error especially with quick motions but produces slower, more conservative motions since it is similar to only doing feedback control without prediction. The other model is a Neural Network \( g_\theta(x_h) \) which takes as input a running history of the current state, \( x_h \), and produces the prediction. This is explained in the next section. The last term of the objective is for smoothing out the control action. The final objective function is then built by adding gains \( G_c, G_f \) and weights \( \alpha, \beta \):
\[
J(x_0, \tilde{u}) = (1 - \alpha) \| G_c (\tilde{x}_c - \tilde{x}) \|^2 + 
\alpha \| G_f (g_\theta(x_h) - \tilde{x}) \|^2 + \beta \| \tilde{u} \|^2
\]
The first two objectives are designed to achieve the same goal, so the weights are designed to be a homotopy with \( 0 \leq \alpha \leq 1 \). Normally, only one of these objectives are active so that \( \alpha = 1 \) or \( \alpha = 0 \). However, when switching, a small transition period is needed where \( \alpha \) is varied smoothly. Meanwhile we only need the last term for smoothing/regularization so: \( \beta << 1 \). The resulting control problem can be solved quickly and efficiently as a quadratic programming (QP) problem.

3. Human motion prediction with neural networks

Human motion prediction with neural networks is also a topic of interest outside robot control, for example in [8, 9]. The implicit assumption is that there is an underlying motion pattern such that given a sufficiently long history of the current motion \( x_h = [x_0 \ldots x_{N-1}] \), we can predict \( x_t = g_\theta(x_h) \) by learning the parameters \( \theta \) of the neural network model \( g \). For example, in our task when most of the letter is written, it should be clear which letter it is and this provides enough context to predict the future motion. A well-known issue here is that the first few predictions will be bad since there is not enough history to provide a proper context yet. This is why we added the conservative model in our MPC and the functionality to switch between models.

The problem of human motion prediction is a well-studied subclass of sequence modeling where Recurrent Neural Networks (RNNs) have shown good results. The Long Short-Term Memory (LSTM) model [10] is the current standard for RNNs and used in benchmarks, for example in [3, 9]. Although these RNN models have shown impressive results in several application areas, one concern here is the training time because all these models require back propagation through time. This is clearly not suited for online learning. At testing time, the forward pass is fast enough to be suitable for the robot control application we present. The disadvantage is that once the model is trained it has to be kept as it is.

Another neural network model that is suitable for time-series prediction is the Dynamic Boltzmann Machine (DyBM) presented in [7]. It is an energy-based model designed for time-series prediction with training speed considerations in mind so it does not use backpropagation through time. It is also designed for online learning for edge devices. Recently, [11] compares a variation of the DyBM with the LSTM and the results are comparable in terms of prediction error. The advantage is that the reported training time of the DyBM is \( 1/16 \) of the LSTM. This is a significant advantage for our target applications.

Apart from the specific architecture of the neural network model, another design choice is the method for training which would dictate the function learned.

We are training the network to do a one-step prediction. To produce the required \( N \)-steps prediction, we use the previous prediction result as the next input. A known issue of this technique is that the predictions will progressively worsen. This does not affect the MPC since it has a structure where later predictions have less weight in the optimization procedure. An advantage of this technique is that \( N \) can be arbitrarily set as the model is independent from it. Lastly, after the \( N \)-steps prediction is created, the internal state of the LSTM and DyBM should be reset to just after the first prediction. This ensures continuity of the real input sequence inside the memory of the NNs.

4. Results and discussion

We evaluate our framework on the human handwriting dataset provided by [6]. The data is composed of the alphanumeric characters and basic math symbols written several times by 11 people. It is already divided into three sets: two training sets and a testing set. Here, we used only the “training1” set consisting of 6590 sequences for training. All the tests and validation are then done using the “testing” set which
has 8136 sequences. The data itself is composed of a series of positions in a 2-DOF coordinate system. As a normalization step, the series of positions are converted to velocities by finite differencing. The pen-up and pen-down events are removed such that there is a large computed velocity during this event. At the end, 5 zeros are appended to learn the concept of stopping after the writing stroke. When training, the networks are reset before a new sequence is shown. Finally, we did not add any distinguishing mark for different characters and we used all the characters to train a single model. This is because we wanted the neural networks to learn a general motion model which is suitable for all the character writing strokes.

For this test, we used one layer of LSTM, with cell state of size 10 and the tanh activation function. This is followed by a fully connected linear layer which produces the output. The Mean Squared Error (MSE) is used as a cost function for backpropagation. The model is trained for 40 epochs, with a batch size of 16 sequences which are zero-padded for uniformity.

As for the DyBM, we used the linear version as the base with three different variations. Firstly, we trained it only offline with the training data. This serves as a comparison with the LSTM, which can only be trained offline for our application. Secondly, we allowed the DyBM to use the testing data for online learning. This is the normal usage of the DyBM. Finally, we added an echo state network (ESN) \[12\], with size 50 and leak parameter 0.7, to the DyBM. This should enhance the non-linearities it can learn while still being fast enough for online learning.

4.1 Neural network inference results

To serve as a baseline for evaluating the results, we used the simplest sensible prediction which is to assume that the velocity will remain constant. A similar model was used in \[8\] as a baseline for predicting human motion. Table 4.1 shows a summary of the results on the testing set. We are using 3 metrics: first the Mean Squared Error (MSE) over the whole validation set. Next, we do a Per-Sequence (PS) comparison. PS-B is the percentage of sequences having an MSE better than the baseline. PS-LSTM is similar but compared against the LSTM.

| algorithm         | MSE | PS - B | PS - LSTM |
|-------------------|-----|--------|-----------|
| baseline          | 3.0875 | ---     | 33%       |
| LSTM              | 3.7132 | 67%     | ---       |
| DyBM offline      | 3.2483 | 39%     | 31%       |
| DyBM online       | 2.7151 | 79%     | 39%       |
| DyBM online and ESN | 2.2715 | 90%     | 42%       |

We can see that for the mean squared error (MSE), the LSTM model and the DyBM trained only offline are both worse than the baseline. However, the DyBMs with online learning are both better. The MSE here is just an indicator of the general model. To investigate further, we did per-sequence comparisons. All the models except for DyBM with offline training are better than the baseline in more than 50% of the 8136 validation sequences. The results here are expected for the DyBMs but somewhat surprising for the LSTM which had a high overall MSE. In checking this further, we observed that the sequences for the same symbols exhibit similar results. The LSTM performed worse in simpler, straighter symbols such as “v”, “1”, “-” but it was better in more complex, curvier symbols such as “p”, “b”, “0” or those with discontinuities from parsing the pen-up-pen-down event like “K”. Since the simple baseline should provide a good approximate for the simple symbols, it is better in these cases. Because the LSTM showed a good performance in the more difficult characters, this led to the comparison of PS-LSTM which is still per-sequence but against the LSTM. In this column, we see that the other methods overachieved LSTM only in less than 50% of the sequences, although the online DyBMs are close at around 40%.

As a summary, the LSTM has learned a highly non-linear model which generalizes to different character strokes but at the cost of being much worse in simple character strokes leading to a high overall MSE. The DyBM trained only offline performs poorly across all metrics, but was not intended to be used in such manner. The online DyBM has learned a general model (high MSE, high PS-B). It is better than the LSTM for simple characters but worse for complex characters. The online DyBM with ESN is the best considering overall performance, but it is still slightly worse than the LSTM on complicated characters.

As for training speed, the LSTM was trained with a batch size of 10 and took around 215 seconds per epoch, while the plain DyBM took around 43 seconds per epoch and with ESN around 54 seconds per epoch. Although not as high as for the dataset reported in \[11\], we see that it is still significantly faster.

4.2 Results of the complete framework

This subsection reports the results on testing the complete framework on simulations of a UR5 robot. Fig. 1 shows some results of the task. For reference, the grid in Fig. 1 has a spacing of 0.1 m. For comparisons of how much the tracking error can be improved, we used a sequence for the letter K as a representative of the results where the baseline performs poorly in terms of MSE. The sequence, taken from the validation set, is played online to represent the human writing the letter. The robot task is to try to write the letter together with the human at the exact same time. To control the robot, the MPC is used to generate the writing motion. This is then used as an end-effector command. Joint trajectory commands are obtained from this by using another QP for doing
inverse kinematics, which handles the joint limits.

Fig. 2 shows a comparison of writing the same sequence in three different ways. First, only the feedback component was used to give a baseline. Secondly, we used one of the trained NN model’s predictions while using the feedforward term all throughout. Lastly, a perfect prediction can be done by using the test sequence in the feedforward term. Although this is practically impossible when the system runs online, it provides an ideal comparison point for the tests here. We can see that the feedback-only case resulted in a tracking error going up to 7 cm. The mean squared tracking error was about 0.0018 m^2. In comparison, we can see a significant improvement by “with prediction” which used the LSTM with the preview horizon of length 10 as a feedforward network for the MPC. Its mean squared tracking error was about 3.12 \times 10^{-5} m^2. This is an order of magnitude better than the feedback-only case. Finally, we compare this result to a perfect prediction, whose mean squared tracking error is about 1.01 \times 10^{-5} m^2. In this ideal prediction case, the error comes from a combination of the preview horizon (optimizing only on a limited time horizon instead of giving the full trajectory at once), the low-level robot motion controllers and the smoothing term of minimizing the jerk. The important point here is that using the NN for the feedforward term can result in tracking errors of the same order of magnitude as the perfect prediction case.

The final test is on using the weights to switch smoothly from feedback only to feedforward. The purpose of this test is to verify that there are no adverse effects due to the switching. The same sequence as those in Fig. 2 was used. The resulting tracking error is shown in Fig. 3. The weight \( \alpha \) was linearly decreased from 1 to 0 during time step 30 until 40. Fig. 3 shows no irregularity during this period where the error decreased as expected.

5. Conclusion

In this paper, we presented a framework that can predict human motions by using different memory-based neural network models and then effectively use these to produce an anticipatory action by using an MPC. Furthermore, separate feedback and feedforward terms were designed to be able to cope with cases when the prediction is unreliable. Finally, we also demonstrated that it is possible to switch between the feedback and feedforward objectives seamlessly. The results show that the presented framework is an effective control strategy for human motion control tracking tasks. Future works on using the same framework for various applications are planned.

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