Online Phase Speed Estimation of Human Motion using a Moving Horizon Estimator

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***Abstract*— To enable intuitive interactions between a robotic device and its human collaborator, the robotic device must be able to anticipate and predict human motion. A crucial aspect to accurately predict human motion is the estimation of the phase speed of a motion. In earlier work, an Iterated Extended Kalman Filter (IEKF) was used to estimate the phase speed. In this work, a Moving Horizon Estimation (MHE) procedure is implemented and compared with the previously proposed IEKF as well as with several other implementations of the phase speed estimation problem. All implementations are evaluated based on their performance to estimate the phase speed of human motions relative to a benchmark. The proposed MHE approach achieves the best performance.**

I. INTRODUCTION

To enable intuitive physical human-robot interactions, a robotic device should be able to recognize and predict the motion of its human counterpart. This is complicated by the temporal and spatial variability displayed by humans when executing motions. Thus, a need arises for "human motion models" that take into account this variability allowing robots to predict motions more accurately. Such models can be found in the Programming by Demonstration (PbD) paradigm in which demonstrations from a human collaborator are encoded and subsequently used to program a robot.

In PbD, several different methodologies have been proposed to encode human motions such as Dynamic Systems [4], Dynamic Movement Primitives [1] and probabilistic Principal Component Analysis [3]. These last two methods use an implicit representation of time. This has the advantage that learned motion models can be temporally scaled. Hence, motions executed slower or faster than the ones used to learn the motion models can still be recognized and predicted.

While an implicit dependency on time allows temporal scaling of the motion models, it requires estimation of two variables related to this implicit representation: the phase (or progress) value of a motion and the phase speed value. The phase speed value is the velocity at which the phase value progresses. This abstract proposes a Moving Horizon Estimation (MHE) procedure to estimate the phase and phase speed value and compares this with a previously proposed procedure based on an Iterated Extended Kalman Filter (IEKF).

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II. RELEVANT WORK

Khansari-Zadeh and Billard propose Stable Estimator of Dynamical Systems (SEDS) to learn motion models. Although the SEDS are robust against (small) temporal variations [4], it is not possible to rescale the time axis of the motion model. In the Dynamic Movement Primitives framework (DMP), it is possible to rescale the time axis [1]. However, the authors do not discuss how to estimate the parameters governing this rescaling. This is imperative when trying to predict human motion.

Apart from dynamical methods, statistical methods have also been proposed to learn motion models such as probabilistic Principal Component Analysis based motion models (pPCA) [3]. The following rescaling of the time axis is proposed in these motion models: $s = v\frac{t}{T_{nom}}$. T_{nom} is the nominal length of a learned motion model, t represents the time and v is the phase speed variable. Using this representation, s (called the phase variable) should always satsify $0 \leq s \leq 1$. v can be used to temporally scale a motion model. To generate predictions for ongoing motions, v and s have to be estimated.

In previous work, a framework was presented to predict human motion [5]. In this framework, an Iterated Extended Kalman Filter (IEKF) estimates v_k at every time step t_k. s_k is then calculated using $s_k = v_k\frac{t_k}{T_{nom}}$. However, the IEKF was often not able to estimate v_k robustly resulting in a lower accuracy for the predicted motions.

This abstract proposes three adaptations to the originally proposed IEKF. First, the process and measurement noise are adapted. Second, the IEKF is transformed into a MHE that takes a window of measurements into account. Third, instead of estimating v_k and calculating s_k using $s_k = v_k\frac{t_k}{t_{nom}}$, an implementation is proposed in which s_k and v_k are estimated together. The final MHE is compared with three other approaches: the initially proposed IEKF, an IEKF with the new values for process and measurement noise and a MHE in which only v_k is estimated.

III. METHODS

The proposed MHE procedure estimates both s_k and v_k leading to a state vector $\boldsymbol{x}_k = \begin{bmatrix} s_k \\ v_k \end{bmatrix}$. The corresponding process model (with process matrix $\boldsymbol{F}$) is:

$$\begin{bmatrix} s_{k+1} \\ v_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} s_k \\ v_k \end{bmatrix} + \boldsymbol{\rho}_{process} \quad (1)$$

With $\rho_{process}$ the normally distributed process noise: $\rho_{process} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{Q})$. The measurement model depends on the type of motion model (such as pPCA motion models or DMP motion models). It is denoted as $\boldsymbol{h}(\boldsymbol{x})$. An observation at time step k is denoted as y_k. The MHE solves at every time instance t_k an optimization problem with following objective function over a horizon with X time steps and with $L = k - X$ (following [3]):

$$\begin{aligned} \min_{x,e_p,e_m} \quad & \boldsymbol{\mu}_0^T \boldsymbol{P}_0^{-1} \boldsymbol{\mu}_0 + \sum_{j=L+1}^{k} \boldsymbol{e}_{p,j}^T \boldsymbol{Q}^{-1} \boldsymbol{e}_{p,j} + \\ & \sum_{j=L}^{k} \boldsymbol{e}_{m,j}^T \boldsymbol{R}^{-1} \boldsymbol{e}_{m,j} \qquad (2) \\ \text{s.t.} \quad & \boldsymbol{x}_{j+1} = \boldsymbol{F}\boldsymbol{x}_j + \boldsymbol{e}_{\boldsymbol{p},\boldsymbol{j}} \\ & \boldsymbol{y}_{\boldsymbol{j}} = \boldsymbol{h}(\boldsymbol{x}_j) + \boldsymbol{e}_{\boldsymbol{m},\boldsymbol{j}} \\ & \boldsymbol{\mu}_0 = \boldsymbol{x}_L - \bar{\boldsymbol{x}}_0 \\ & lb \leq \boldsymbol{x}_j \leq ub \end{aligned}$$

$\boldsymbol{R}$ denotes the measurement noise covariance matrix. The first two constraints enforce the process and measurement model. The first term in the objective function (along with the third constraint) represents the arrival cost. This cost models the cost of all elements outside the window and is set using the same procedure as in Tanghe [3]. The final constraints specifies the bounds on the state. These are $0 \leq s_k \leq 1$ and $0 \leq v_k$.

In this work, motion models are learned with the probabilistic Principal Component Analysis method. The corresponding measurement model can be found in the thesis by K. Tanghe along with a procedure to derive a parameter σ_{ML} such that the measurement noise covariance matrix can be set equal to $\boldsymbol{R} = \sigma_{ML}^2 I$ [3]. The IEKF formulation proposed in earlier work used this setting for $\boldsymbol{R}$. The process noise covariance matrix was set to $\boldsymbol{Q} = 10^{-6}$ (this is a scalar as the IEKF only estimates variable v_k). In all new implementations, the process noise covariance matrix is set according to [6] and the measurement noise covariance matrix is set as:

$$\boldsymbol{R} = \begin{bmatrix} (4\sigma_{ML})^2 & 0 \\ 0 & (4\sigma_{ML})^2 \end{bmatrix} \qquad (3)$$

IV. Experiments and Results

94 squat demonstrations of eight different subjects are used to evaluate the phase speed estimation approaches. The demonstrations contains hip flexion and shoulder elevation angles. Demonstrations from seven subjects were used to learn a motion model. Demonstrations from the remaining subject were used to evaluate the algorithms. This was done in such a way that every subject was once excluded from the training data set.

Six different implementations of the phase speed estimation problem are evaluated (see table I) and compared with a benchmark. The benchmark is calculated using the proposed MHE estimation but with a window length equal to the length of the full demonstration. Hence, the benchmark can be considered as a global optimum.

Comparison is done based on the cumulative squared euclidean distance between the estimated and benchmark value of v_k at every time instance t_k in a demonstration and averaged over all 94 trials. Moreover, the average duration of an estimation at one time step is reported as well.

TABLE I
Comparison of different formulations

		Av. duration [s]	Av. difference [-]
IEKF: 1 state	old	0.00301	28.188
	new	0.00341	11.104
MHE: 1 state	$X = 1$	0.00318	10.307
	$X = 10$	0.00443	10.488
MHE: 2 states	$X = 1$	0.00308	10.031
	$X = 10$	0.00499	10.137
Benchmark		0.139	N.A

The first evaluation ("IEKF: 1 state old") refers to the IEKF from earlier work. The second one is the same IEKF but with measurement and process noise described in the previous section. The third and fourth implementation are MHE implementations with only one state (v_k) and with horizon length X set to $X = 1$ or $X = 10$. Finally, the MHE implementation with two states proposed here is evaluated with a horizon containing one and ten elements.

As can be seen, the two state MHE formulation leads to the lowest average difference with the benchmark. Somewhat surprisingly, a horizon with ten elements leads to a higher average difference than a horizon with just one element. However, it is possible that a value between one and ten leads to an even lower average difference. Second, the average duration is highest for the two state MHE implementation. This is to be expected as more variables are being estimated in this formulation. Finally, adapting the noise parameters results in the largest reduction of the average difference.

V. Conclusions

A Moving Horizon formulation of the phase speed estimation problem has been proposed and evaluated on human motions. Six different formulations of the phase speed estimation problem are compared with a benchmark. The MHE with two states outperforms all other formulations. A suitable choice for the window length could further improve the results. However, a higher window length also leads to higher computational load.

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