

# Velocity-Based Multiple Change-point Inference for Unsupervised Segmentation of Human Movement Behavior

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**Abstract**—In order to transfer complex human behavior to a robot, segmentation methods are needed which are able to detect central movement patterns that can be combined to generate a wide range of behaviors. We propose an algorithm that segments human movements into behavior building blocks in a fully automatic way, called velocity-based multiple change-point inference (vMCI). Based on characteristic bell-shaped velocity patterns that can be found in point-to-point arm movements, the algorithm infers segment borders using Bayesian inference. Different segment lengths and variations in the movement execution can be handled. Moreover, the number of segments the movement is composed of need not be known in advance. Several experiments are performed on synthetic and motion capturing data of human movements to compare vMCI with other techniques for unsupervised segmentation. The results show that vMCI is able to detect segment borders even in noisy data and in demonstrations with smooth transitions between segments.

## I. INTRODUCTION

The artificial imitation of human movement behavior in robotics is a challenging problem. Solving a task like grasping a cup can easily be performed by humans independent of, e.g., the orientation of the cup. For a robot, even minor changes to the task or the objects involved could require the use of new, accordingly adapted control mechanisms. With increasing complexity of the task, the control of robot movements gets even more challenging. In recent years, new methods to simplify movement generation in robotic systems have been proposed, which use learning techniques to transfer human demonstrations of complex behavior to a robot [1]. In this research area called “Learning from Demonstration” (LfD), most state-of-the-art methods are monolithic learning approaches, i.e., they learn one behavior that covers the whole demonstration. With these approaches, learning can be very time consuming or even impossible if complex behavior should be learned.

Learning of complex behaviors in humans takes place incrementally, as shown in behavioral studies in, e.g., infants [2]. This means that smaller individual building blocks are learned separately and later combined to a single, higher level complex behavior. This process is called chunking of action repertoires [3]. When learning novel behaviors, formerly learned building blocks might be re-used and can accelerate the learning process. This principle of learning performs better

than monolithic learning approaches, i.e., allows learning more complex behavior [4]. To learn complex behavior in a robotic system with LfD, segmentation techniques are required to divide demonstrations into behavioral blocks, which can be learned individually and transferred to a robot.

In this paper, we propose an algorithm which segments a trajectory of a human movement demonstration into its behavior building blocks in a fully automated fashion. Ideally, these building blocks should represent ‘primitive motions’ from which a wide range of behaviors can be generated. Although the question of what a primitive human motion is remains open in the literature, Morasso made interesting observations in human arm movements which give a meaningful basis for a segmentation into primitives [5]. He observed in human point-to-point arm movements piece-wise planar hand trajectories which had characteristic, bell-shaped velocity profiles. Based on these observations, we propose a segmentation method which uses the position and the velocity trajectories of the hand as indicators for segmentation points. To our knowledge, the proposed algorithm is the first unsupervised behavior segmentation algorithm, which includes velocity patterns into the segmentation process to find meaningful behavior segments which have a clear relation to potential movement primitives.

The automatic segmentation of human behavior into behavior building blocks comes along with several problems. Demonstrations of the same behavior can be performed with a large inter-subject as well as intra-subject variability. Therefore, a segmentation algorithm is required which is able to, e.g., handle different segment lengths resulting from movements demonstrated at varying speeds. Our proposed algorithm is based on Bayesian inference, where noise in the recorded movement can be integrated into the model. The segmentation algorithm is based on an online variant of an algorithm to detect change-points in time-series data by Fearnhead and Liu [6], called *Multiple Change-point Inference* (MCI). We have extended this approach to a velocity-based MCI (vMCI), in which the velocity profiles, as observed by Morasso [5], are integrated into the segmentation process.

The state-of-the-art algorithms for behavior segmentation are discussed in Section II. The methods we use are explained in Section III, starting with an explanation of the used representation of behavior segments (III-A), the online variation of the original MCI (III-B), and finishing with the presentation of our proposed extension of MCI where velocity patterns in

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movement demonstrations are used to find segmentation points in Section III-C. Afterwards the performance of the proposed vMCI is compared with other segmentation methods in several experiments. At the end, a conclusion and an outlook for future research topics is given.

## II. RELATED WORK

Segmentation of time series data and recognition of human actions is an active research area with many different applications and algorithms. Most of these algorithms are supervised [7] and for this reason not applicable if the searched behavior segments are not known in advance. Instead, unsupervised algorithms are needed to segment a time series into its behavior blocks. A heuristic approach for automatic segmentation is presented by Fod et al. [8], where segment points are detected if the angular velocity of several degrees of freedom (DOFs) crosses zero. This approach is very sensitive to noise and tends to over-segment the data, in particular if many DOFs are considered as data input. A similar approach is proposed by Jenkins and Matarić [9], who use *Kinematic Centroid Segmentation* to detect ‘swings’ in the velocity of joint angle data. Here, as well as for the detection of zero velocity crossings, a threshold has to be chosen which may change if a different movement is analyzed.

Other approaches use probabilistic models to segment behavioral data. This bears the advantage that variations in the movement execution can be integrated into the data model as presented for example by Chiappa and Peters [10]. Their method is applicable without manual a segmentation of training data, but the number of segments has to be determined in advance or by, e.g., cross-validation. An example for a probabilistic segmentation which does not require a priori knowledge is given by Kohlmorgen and Lemm [11], in which a behavior segment is modeled with a HMM built from a windowed data sequence in an online fashion. An extended version is used by Kulić et al. to segment and cluster full body motions [12]. On the other hand, Fox et al. model a behavior segment with a linear regression model and infer segment borders with the so-called *beta process autoregressive HMM* (BPARHMM) [13]. Their inference model allows for shared regression models, i.e., the resulting segments are segmented and clustered at the same time to identify repeated building blocks of the same movement. Niekum et al. used the BPARHMM algorithm to segment kinesthetic demonstrations provided by hand-coded controllers of a pick-and-place task [14]. The MCI algorithm, which served as a starting point for the method we propose in this paper, is a similar segmentation method which works without a priori knowledge of the number of segments. Furthermore, it has a data model that allows to integrate characteristic velocity patterns into the segmentation. It is also used by Konidaris et al. [15] to segment trajectories recorded by maneuvering a robot through a corridor.

## III. METHODS

### A. Bayesian Linear Regression Models for Data Representation

In the MCI algorithm as well as in our extension to a velocity-based MCI, behavior blocks are represented with linear regression models (LRMs) and Bayesian inference techniques are used to determine the model parameters. A detailed

introduction to Bayesian linear regression is, e.g., given by Bishop [16]. Below, we give a short introduction to this data representation.

We assume that a data sequence,  $y = (y_1, \dots, y_n)$  of length  $n$ , with  $y_i \in \mathbb{R}^d$  being an observation at time point  $i$ , consists of an unknown number of segments. The segments are modeled independently of each other with linear regression models (LRMs). A LRM is a weighted sum of  $q$  basis functions  $\phi$  with added noise. A segment  $y_{i+1:j} = (y_{i+1}, \dots, y_j)$  starting at time point  $i+1$  and continuing until time  $j$  is modeled by

$$y_{i+1:j} = \sum_{k=1}^q \beta_k \phi_k + \varepsilon = H\beta + \varepsilon. \quad (1)$$

$H$  is a  $(j-i) \times q$  matrix of basis functions  $\phi$ ,  $\beta = (\beta_1, \dots, \beta_q)$  are the model parameters, and  $\varepsilon$  is a vector of independent and identically distributed Gaussian noise with zero mean and variance  $\Sigma$ . To infer the model from the data, prior distributions are set over the weights and the noise variance. The parameters  $\beta$  are assumed to be matrix-normal distributed with zero mean and covariances  $D$  and  $\Sigma$  along rows and columns respectively. To ensure direct calculation of the posterior probability of the data, conjugate priors are assumed. This results in an inverse Wishart prior for the variance  $\Sigma$  with parameters  $\nu$  and  $S$ . The likelihood of the data sequence  $p(y_{i+1:j}|m)$  given the model  $m$  of order  $q$  can be derived by marginalizing out the model parameters  $\beta$ , i.e.,

$$\begin{aligned} p(y_{i+1:j}|m) &= \int p(y_{i+1:j}|\beta, \text{model } m)p(\beta) d\beta \\ &= \int \int p(y_{i+1:j}|\beta, \Sigma) \cdot p(\beta|D, \Sigma) \\ &\quad \cdot p(\Sigma|\nu, S) d\Sigma d\beta, \end{aligned} \quad (2)$$

as derived and explained, e.g., by Bishop [16].

### B. Online Multiple Change-point Inference (MCI)

Fearnhead and Liu [6] presented several methods to directly infer segment borders and models from the posterior for the data representation of the previous section. In this section we present their proposed online inference algorithm and later on, in Section III-C, expand it to determine behavior segments in a demonstrated trajectory based on the velocity profiles.

Fearnhead and Liu treat a segment border as a change-point which refers to a time point  $i$  in the series  $y$  where the underlying LRM changes. The segment models are assumed to be independent of each other. The change-point positions are modeled via a Markov process where the transition probabilities are dependent of the segment length between two change-points:

$$P(\text{next change-point at } j | \text{change-point at } i) = g(i-j). \quad (3)$$

Here,  $g(l)$  is the probability of a segment having length  $l$ . The cumulative distribution function of this length is given by  $G(l) = \sum_{k=1}^l g(k)$ . As proposed by Konidaris et al. [15], we assume a geometric distribution for  $g(l)$ , so that  $g(l) = (1-p)^{l-1}p$  and  $G(l) = 1 - (1-p)^l$ . Using these distributions, the parameter  $p$  regulates the expected segment length, which is  $1/p$ .

To determine the most probable change-point positions and segment models for an observed data sequence, an online Viterbi algorithm is proposed by Fearnhead and Liu [6]. For each time point  $t$ , the algorithm calculates the most likely change-point position  $j$  prior to  $t$  and the most likely model of this segment from  $j$  to  $t$ . This is done by determining the posterior probabilities for each segment which ends at  $t$  and for all data models. The algorithm calculates for each  $t > 0$ ,  $j = 0, \dots, t - 1$ , and every model  $m \in \mathcal{M}$ :

$$P_t(j, m) = (1 - G(t - j - 1))p(y_{j+1:t}|m)p(m)P_j^{MAP}, \quad (4)$$

and

$$P_t^{MAP} = \max_{j, m} \left( \frac{P_t(j, m)g(t - j)}{1 - G(t - j - 1)} \right). \quad (5)$$

Equation (4) gives the probability that the most recent change-point prior to  $t$  occurs at time  $j$  with model  $m$  for the segment  $y_{j+1:t}$  that has a length of at least  $t - j$ . The first term is the probability that the assumed segment starting at  $j + 1$  has a length of at least  $t - j$ . It is multiplied with the marginal likelihood of that segment having model  $m$ ,  $p(y_{j+1:t}|m)$ , times the prior probability of the model  $m$ ,  $p(m)$ . The last term  $P_j^{MAP}$  denotes the most likely change-point position prior to  $j$ . In Equation (5) the most probable  $j$  and  $m$  are determined. We chose the initial  $P_0^{MAP}$  to be  $1/|\mathcal{M}|$ . Because the probabilities  $P_t(j, m)$  are very close to zero for most of the possible segments, a particle filter as proposed by Fearnhead and Liu can be used to reduce computation time [6].

### C. Segmentation of Velocity Profiles using Velocity-Based MCI

To account for the bell-shaped velocity profiles in point-to-point movements as observed by Morasso [5], we extended the MCI to a velocity-based MCI (vMCI). For this, we modified the data representation of Section III-A and adapted the MCI algorithm to infer change-points using this new representation. We propose to split the data model given in Equation (1) and model different data dimensions with different basis functions. More precisely, we assume that the data sequence  $y = (y_1, \dots, y_n)$ ,  $y_i \in \mathbb{R}^d$ , consists of one dimension with the absolute velocity in the direction of movement, denoted as  $y^v$ . This dimension is modeled separately with a special basis function, which approximates a bell-shaped structure. Using this model, the assumption that one segment is characterized by an increasing velocity at the start and a decreasing velocity at the end can be integrated into the segmentation process. Note that this approach does not require the velocity to become zero between segments, unlike other methods for automatic segmentation. Furthermore, inaccuracies in the movement trajectory can be handled because of the integrated modeling of noise.

The velocity  $y^v$  of the observed data sequence is modeled by

$$y^v = \alpha_1 \phi_v + \alpha_2 + \varepsilon. \quad (6)$$

As in the original LRM, the weights  $\alpha = (\alpha_1, \alpha_2)$  and the noise  $\varepsilon$  are matrix-normal distributed with  $\alpha \sim \mathcal{MN}(0, D_v, \Sigma_v)$  and  $\varepsilon \sim \mathcal{MN}(0, I, \Sigma_v)$ .  $D_v$  and  $\Sigma_v$  are the prior parameters. The prior distribution of  $\Sigma_v$  is again chosen to be inverse Wishart,  $\Sigma_v \sim \mathcal{IW}(\nu_v, S_v)$ , to provide conjugate priors. The model order is fixed to 2, with the two basis functions  $\phi_v$  and 1. The constant weighted with  $\alpha_2$  is

added to account for velocities unequal to zero at start or end of the segment. To modulate the velocity,  $\phi_v$  is chosen to be one single radial basis function with center  $c$  and width  $r$  because of its bell-shaped structure. Thus,

$$\phi_v(x_t) = \exp \left\{ -\frac{(c - x_t)^2}{r^2} \right\}. \quad (7)$$

Whereas the MCI algorithm determines the best fitting LRM of Equation (1) out of a set of different models defined by different orders  $q$ , the possible velocity LRMs of Equation (6) differ in their center position  $c$ . For example, a center location closer to the starting point of the segment allows to approximate a segment with high velocity at the beginning and rather low velocity at the end. The width parameter  $r$  is chosen to be half of the assumed segment length, i.e.,  $r = (t - j - 1)/2$ , such that the whole segment can be covered by the model.

To infer the segment borders and model parameters from the data with different LRMs for different data dimensions, one can proceed as explained in the previous section with the online Viterbi algorithm. The set of possible models  $\mathcal{M}$  now consists of every combination of models for the velocity dimension as well as models for the remaining data dimensions. Only the model evidence of Equation (2), which gives the fit probability of a certain model to the data has to be adapted. As we assume independent models for the velocity and the rest,  $p(y_{i+1:j}|m)$  is now defined as a product of the model evidences of both linear regression models. They can be calculated using the formula given in Equation (2) with parameters  $D, S$ , and  $\nu$  or  $D_v, S_v$ , and  $\nu_v$  for the velocity dimension, respectively.

## IV. EXPERIMENTS

We present several experiments to evaluate the performance of vMCI and to compare it to other segmentation algorithms. In general, the comparison of different behavior segmentation algorithms is difficult because a ground truth segmentation is not available in natural human movements. For this reason, it is desirable that the influence of the parameters of the algorithm is low such that they can be fixed or calculated from the data because an optimization, e.g., via cross validation, is in general not possible. Hence, we show in a first experiment the reduced parameter influence of vMCI in comparison to the original MCI and the *beta process auto-regressive hidden Markov model* (BPARHMM) [13]. The experiment was performed on synthetic trajectories consisting of two segments, where the ground truth is known. In the second set of experiments, described in Section IV-B, human movements were recorded with a motion capture system to obtain realistic demonstrations of human behavior. In these experiments, the capability of vMCI to segment a demonstration into behavior building blocks characterized by bell-shaped velocity patterns is shown. In the first motion capture experiment, demonstrations were recorded in a restricted environment which only allows for variations in the movement velocity. There we show that our proposed vMCI methods performs better than a naive segmentation method which searches for local velocity minima. In a last experiment, the ability of vMCI to scale to free human movements is shown on ball-throwing demonstrations.

In all experiments, the basis functions  $\phi$  of the LRM are chosen to be autoregressive with order  $q = 1$ , i.e.,

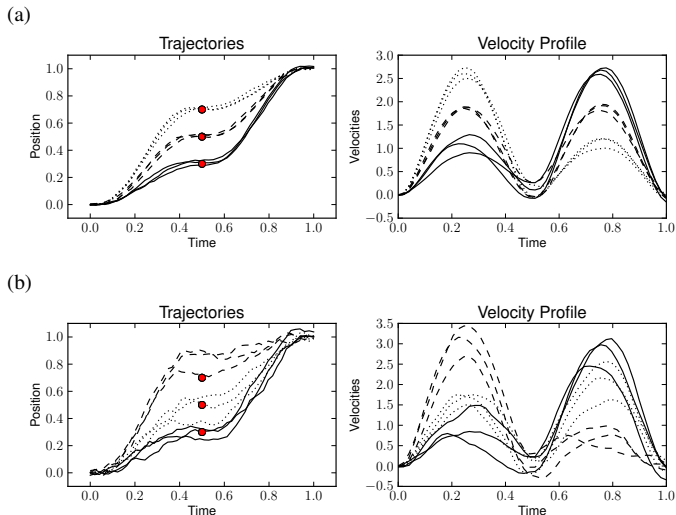


Fig. 1. Two datasets of sequenced DMPs. (a) Trajectories of three demonstrations for each of three possible subgoal positions (red points) with their corresponding velocities which were varied at the subgoal positions. (b) Trajectories with corresponding velocities of the second DMP dataset with added noise.

$\phi(x_t) = y_{t-1}$  for time  $x_t$  in Equation (1). The data dimensions modeled with this basis are pre-processed to a mean of zero and such that the variance of the first order differences of each dimension is equal to 1. The parameter for the distribution of the segment length  $p$  in the MCI and vMCI algorithm is fixed to  $p=0.02$  because it has, due to the Bayesian model of the algorithm, a small influence on the segmentation results.

### A. Segmentation of Sequenced DMPs

In this experiment, we compare vMCI with other unsupervised segmentation methods on synthetic data with different parameter configurations to show the reduced influence of the parameters due to the integration of the velocity into the segmentation process. The synthetic dataset consist of two consecutive *dynamical movement primitives* (DMPs) [17]. With this, the ground truth segmentation point between the two DMPs is known which makes a comparison of the algorithms possible. DMPs are a popular representation of behavior building blocks in LfD domains. They describe a movement using a dynamical point attractor system, from which arbitrary shape-able, goal-directed movements can be generated.

Using DMPs, two datasets were generated, each consisting of 9 trajectories which are concatenations of two DMPs of the same length. The first dataset contains 3 demonstrations for each of 3 different subgoal positions between the two DMPs. In the second dataset, Gaussian noise was added to simulate variance in the movement execution. The DMP sequences have different velocities at the subgoal positions. To generate the trajectories, the DMP representation by Mülling et al. [18] was used where the goal velocity can be modified to a desired value. In Fig. 1 the generated trajectories are shown with their corresponding velocity.

Using this dataset, vMCI was compared to the conventional MCI and to the BPARHMM algorithm by Fox et al. [13] introduced in Section II. The BPARHMM uses the same data model as MCI and has a set of equal parameters. This

TABLE I. MEAN SEGMENTATION RESULTS ON SEQUENCED DMP DATASET (WITH NOISE).

	F1-measure	number true positives (avg., optimal: 1)	number false positives (avg., optimal: 0)
vMCI	0.89 (0.85)	0.96 (0.93)	0.23 (0.29)
MCI	0.41 (0.20)	0.61 (0.25)	0.87 (0.38)
BPARHMM	0.68 (0.63)	0.98 (0.86)	1.34 (1.10)

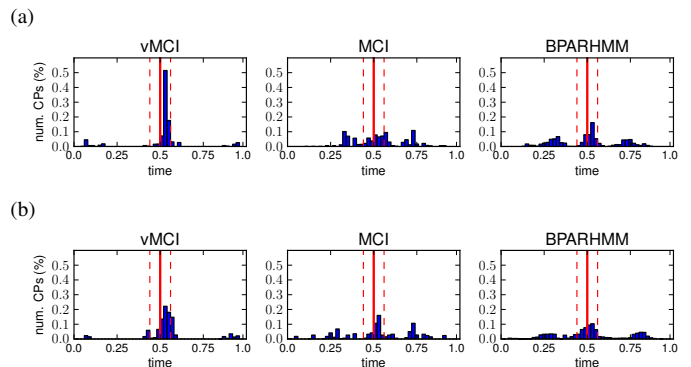


Fig. 2. Distribution of detected segmentation points by different algorithms with different parameter configuration. The true segment border is marked with a solid horizontal line. Segmentation points detected in a margin around this point (dashed lines) are treated as correct. (a) Results on DMP dataset. (b) Results on noisy DMP data.

allows us to compare the algorithm with the same set of parameter configurations. Furthermore, the BPARHMM is used for comparison because it showed promising segmentation results in the literature [14]. An open-source implementation is available<sup>1</sup>.

The three algorithms were compared on the two synthetic DMP datasets with different parameter configurations. The hyper-parameters  $D$ ,  $S$ , and  $\nu$ , influencing the prior distributions of the model parameter  $\beta$  and the noise variance, of the three segmentation algorithms were varied in the following ranges:  $D \in [1, 5, 10, 20]$ ,  $S \in [0.1, 1, 10, 25]$ , and  $\nu \in [4, 6, 8]$ . This results in  $4 \cdot 4 \cdot 3 = 48$  different parameter configurations for each demonstration. The other parameters were chosen as suggested in the original publications. Note that due to a more complex inference method, the calculation time of BPARHMM segmenting the synthetic dataset is approx. 20 times larger than the calculation time of the same data with the proposed vMCI.

In Fig. 2 the position of the obtained segment borders of all parameter configurations and all 9 demonstrations are shown in a histogram for each of the segmentation algorithms. The segmentation accuracy determined with the F1-measure and the number of true and false positives for each algorithm are listed in Table I. The results show that vMCI detects the correct position of the segment transition more accurately than MCI and BPARHMM. Although BPARHMM outperforms the conventional MCI, it shows more false positives than vMCI if the parameters are varied. This means that with the integration of the velocity profiles into the MCI, the segmentation results become more robust with respect to parameter selection. This holds true for different subgoal velocities as well as when adding noise.

<sup>1</sup><http://stat.wharton.upenn.edu/ebfox/software>

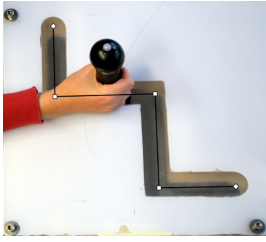


Fig. 3. Reference testbed for motion capturing. The subject was instructed to move the stick from the top left position through the path and back to the start, if possible without hitting the edges. The expected behavior segments lie between two corners of the figure, marked with white squares in the image.

### B. Motion Capture Experiments

To evaluate vMCI on human behavior, two series of demonstration experiments were conducted. In the first set of experiments, a subject sitting in front of a 80x80 cm table being covered by 6 motion capture cameras was instructed to move a stick through a step-like path (see Fig. 3). The movements were captured with a marker placed at the top of the stick with a resolution of 500 Hz, which was down-sampled during pre-processing to 25 Hz. The subject had to move the stick with her/his right hand through the path and back to the start position without hitting the edges. The setup was designed in a way that the main difference between the demonstrations lies in the velocity. It is assumed that the movement is slowed down at the corners of the path, which mark the expected segment borders. The velocities in the movement direction of the three demonstrations are shown in the first row in Fig. 4. The points in time when the stick passed the corners are marked with horizontal lines. As expected, the segments between the corners show bell-shaped velocity patterns.

Three demonstrations were recorded, consisting of the 3-dimensional position of a marker placed on top of the stick and its velocity. The recorded data was automatically segmented with vMCI. The parameters were fixed or calculated from the data, because of their small influence, as shown in the previous experiment. The parameter  $D$ , which regulates the variance of the model parameters  $\beta$  along the data dimensions, is set to the identity matrix. This is a good choice because an autoregressive basis is chosen and the data is pre-processed to a variance of one. The parameters  $S$  and  $\nu$  influence the variance of the weights as well as the Gaussian noise of the LRM along the time dimension. These parameters can directly be calculated from the data to estimate the true variance by determining the variance of the first order differences of the data along the time dimension.

The results of the segmentation of the reference demonstration with vMCI are depicted in the middle row of Fig. 4. The LRMs for the velocity with the highest probability are shown as a green dotted line. The velocity of each segment is successfully approximated with the model of Equation (6), despite any noise in the data. For comparison, the dataset was additionally segmented with a naive baseline approach which detects a segmentation point in the data at positions where a local minimum occurs in the velocity in a window of 5 time points (0.2 seconds). In the results shown in the lower row of Fig. 4, one can see a high number of false positive segmentation points due to the noise contained in the data.

TABLE II. MEAN SEGMENTATION RESULTS ON STEPS DATASET.

	F1-measure	number true positives (avg., optimal: 9)	number false positives (avg., optimal: 0)
vMCI	0.93	8.33	0.67
local minima	0.60	8.67	11.33

The segmentation performance shown in Table II confirms this visual impression. Although the effect of over-segmentation could potentially be reduced by choosing a larger time window to find the minima, this segmentation method could not be used with other demonstrations containing different levels of noise without manual adaption, while this is possible with vMCI.

In a last experiment the capability of vMCI to detect meaningful segments in a free, natural movement is analyzed. A subject with markers placed at the arm and the hand was instructed to throw a small ball into a box. The demonstration was captured with 5 cameras, again with a resolution of 500 Hz, down-sampled to 25 Hz. This movement can be divided into three main phases: a strike out, followed by the actual throw, and a final movement bringing the arm back to its initial position. The segmentation with vMCI was performed on the position and velocity of the marker placed on top of the hand of the subject. The representative segmentation result of one demonstration is shown in Fig. 5. The velocity of the demonstration shows again bell-shaped curves, one for each of the three main throwing segments and two belonging to a settle down-phase at the end of the movement. As indicated by the vertical lines, it was possible to detect these segments using vMCI.

## V. CONCLUSION

With the velocity-based MCI approach, we presented an algorithm for unsupervised segmentation of behavior demonstrations which successfully detects behavior building blocks with bell-shaped velocity patterns, which are assumed to be characteristic for primitive motions in human arm movements. The performed experiments show that the algorithm is robust against noise and can handle variations in the movement execution more effectively than other methods for unsupervised segmentation. Furthermore, the influence of the parameters could be reduced which makes the algorithm applicable to different datasets where the required manual user input is reduced. The experimental data gained from human demonstrations were designed in a way that the movements could be naturally performed, without artificial integrated pauses between assumed behavior blocks. Nonetheless, the vMCI detected meaningful segments which corresponds to the assumed building blocks.

Although the segmentation was performed only on the position and velocity of a single marker in the presented experiments, the presented vMCI algorithm could be used in future work to segment data gained by multiple markers. Furthermore, other data, like joint configurations, could be used by designing other basis functions which fit characteristic patterns of this data.

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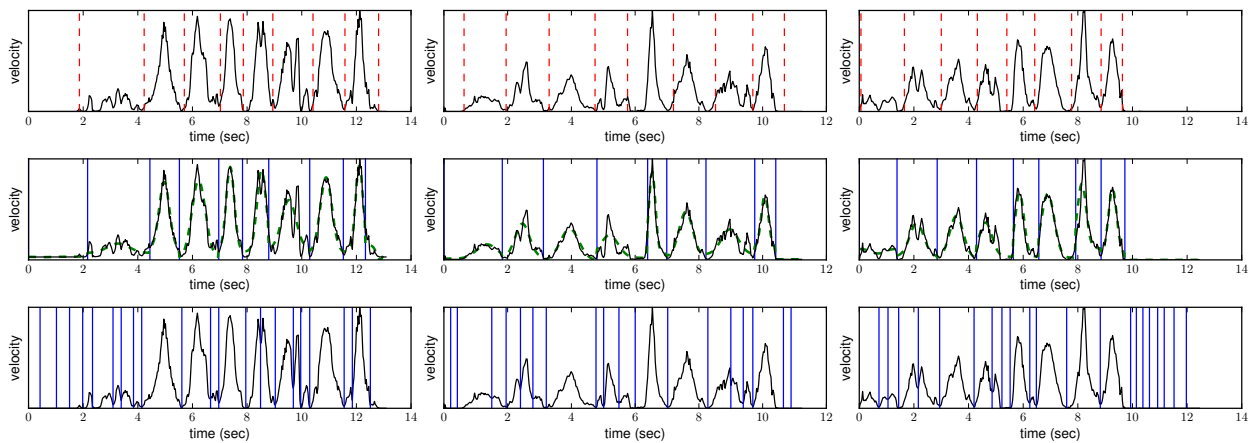


Fig. 4. Segmentation of 3 demonstrations of step-like reference testbed. The top row shows the velocity of the demonstration with the ground truth segmentation at the corners of the path. In the middle, the segmentation points resulting from vMCI are shown, and in the bottom row the results obtained with a naive segmentation approach based on the search for local velocity minima. The results show, that vMCI is more robust against noise as the naive approach.

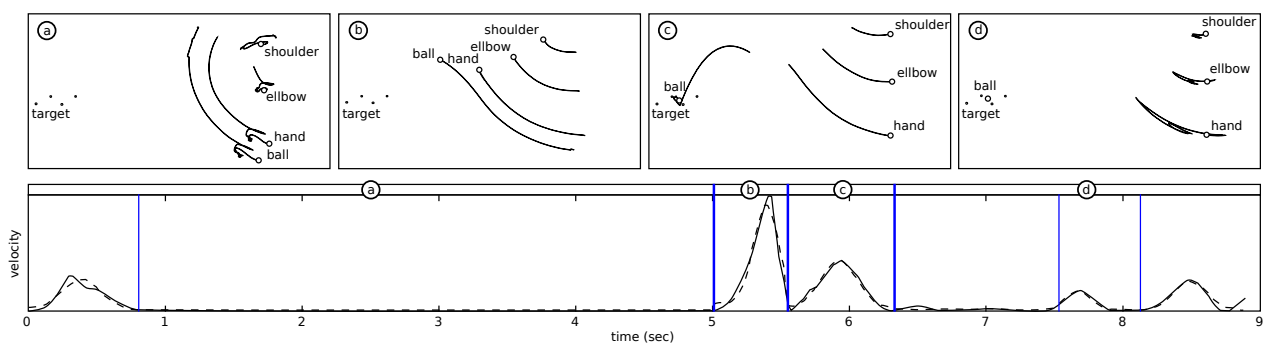


Fig. 5. Segmentation of a throwing demonstration. The first row shows the marker positions: (a) strike out movement with waiting posture, (b) actual throw, (c) swinging out, (d) some small swings at the end of the movement. The circles mark the last point of the movement in each image. Below, the velocity of the marker on the hand is shown with vMCI segmentation points (horizontal lines) and approximation of bell-shaped curves for each segment (dashed line). Each of the ball throwing phases are successfully detected by the algorithm.

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