Interaction Learning

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Abstract

The robot is becoming more and more part of the normal life that emerged some conflicts, like: How could a safe physical human robot interaction happen and what kind of problems had to be solved for a successful interaction? This paper describes a scenario of interactions between human and robots and it pointed out the improvement of the robot motion using a machine learning algorithm based on Gaussian mixture models.

1 Introduction

The modern world robotic systems mostly remained in the realm of industry or academic research. Recently produced robot systems are specialized e.g. for the automation industry to produce with high frequency and without endangering human employees. Also there are highly realistic android robots and as the result of the ongoing process of development and research the robots expand to other areas of life such as offices. This expansion lead to the question - How could human and robot interact successfully? - The interaction between humans and robots – e.g. lifting a box together - is one of the biggest challenges for modern science. There are problems to be solved for a successful interaction like adaption to human behavior. Therefore a close contact is required in which the safety had to be guaranteed at all times. Furthermore the robot should react adequately e.g. based on the force the human interaction partner is using. Additionally the behavior of the robot had to be improved using a machine learning algorithm, which is still the most difficult task for physical human robot interaction caused on the different kinds of motion each human has.

In this paper I present the related work on human robot interaction and also the machine learning algorithms which are used. Despite various obstacles the human robot interaction achieved successes which are also presented. In the end an outlook will point out some possible ways for further researches.

2 Related Research

Necessary and important aspects of the human-robot interaction have been researched for decades. A research project conducted by the European Network of Excellence (EURON) [1] focused on the discussion of important requirements for physical human robot interaction (PHRI) to be safe. The follow-up project was initiated to achieve more of the required aspects to be intrinsically safe. To achieve this goal new control algorithms and concepts are needed, as shown in [2]. Even extraordinary methods such as testing the impact force on crash test dummies [3] were used. However, there is no focus on learning or adaptation between humans and robots.

Another possibility of doing a safe human robot interaction is to improve the sensors like using a new developed modern soft skin for robot to sensing the interaction all over the body as described in [7].

Another way to modeling interaction is shown in [14]. This work presents the principle of maximum causal entropy, an approach based on causally conditioned probabilities. There are several outer animation based interaction learning algorithms like [15], unfortunately they are invented for animation and could not get transfered to a human robot interaction in a simple way.

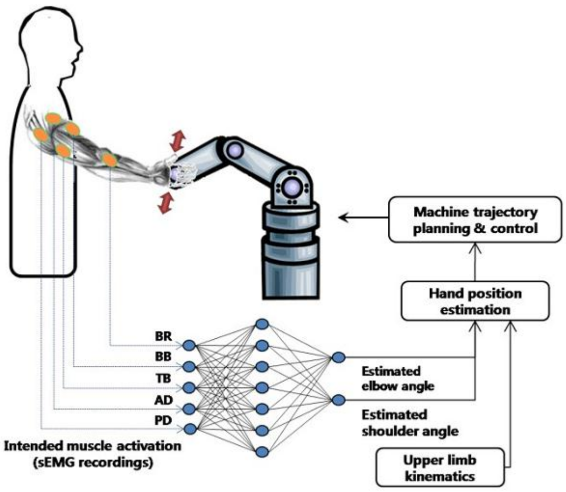

Figure 1: process overview [13]

One promising approach for human robot interaction described by Kwon S. et al. [13] is based on surface electromyography (sEMG) signals. These signals are collected and processed by an artificial neural network algorithm, trying to predict the motion of the human partner. The human and robot are shaking hands, and learning. The result also demonstrated that the manipulator began to move almost simultaneously with the movements of the human partner.

In [9] a different entry of interaction learning is presented using four key issues with a solving strategy displayed in the table below.

Key issue	**Solution**
motion imitation	marker control
understanding motion primitives	mimesis model
understanding interaction primitives	mimetic communication model
physical contact establishment	real-time motion reshaping and impedance control

Table 1: key issues and solutions

The marker control represents a simple human motion imitation and also the learning algorithms are designed for imitation of a human and active involvement. By modifying the communication mimetic they achieve communication in physical domain as well as the symbolic domain. In the physical domain the motion accordance with the human's motions in real-time. The learning algorithm in this paper is based on the hidden markov model (HMM), which is quiet similar to the used algorithm described in this paper.

The following parts of this paper are mostly based on the work of Amor et al. [4], providing a good overview of the topic.

3 Human-Robot Interaction

Human and robot are working together to achieve one common goal. Figure 1 gives an overview about the interaction. After the interaction the human partner should give a feedback whether the interaction was a successful or not. This may happen in various ways, e.g. by using a graphical user interface. This feedback information is stored and used for learning after a data optimization step. It is a human-in-the-loop learning system, which means that the human as well as the robot are reacting to each other. Passing some iteration the collected data is projected on a low-dimensional manifold, this reduces the calculation load and also stabilizes the learning by reducing the influence of some outliners. For each set of data a Gaussian Mixture Model (GMM) is learned. By computing the likelihood it is possible to choose, which action to perform. The more learning loop iterations the better is the action performed by the robot.

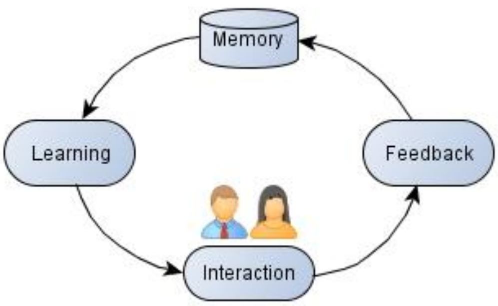

Figure 2: physical interaction learning (like [4], p. 3)

4 Learning

The following part describes the machine learning algorithm, which is used in [4]. To demonstrate the algorithm a child-robot had the task to stand up with the help of a human. This task can be divided into three different postures. The first one in which no action occurs. Then the first switching posture, where the arms are pulled by the human partner and finally the second switching where the legs are bent more. This sequence also dictates the desired postures, the possible postures and a set of control desired postures.

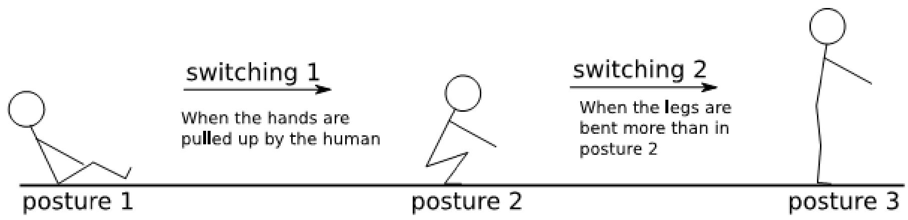

Figure 3: three desired postures in the standup task [4]

The goal of this task is the timing between the switching of actions between different desired positions. The robot posture is a 52-dimentional vector that contains the current angels of each joint. The Database holds the last ten iterations by overwriting the old data or the unsuccessful action loop. After these ten iterations the data is used for learning with the goal of optimally changing the action to reach the new desired posture during the sequence. Therefore a GMM is used which produces a probabilistic model to indicate the desired posture based on the current position. At the beginning the dimension of posture vector is reduced using a principal component analysis (PCA) [4], [15], [16].

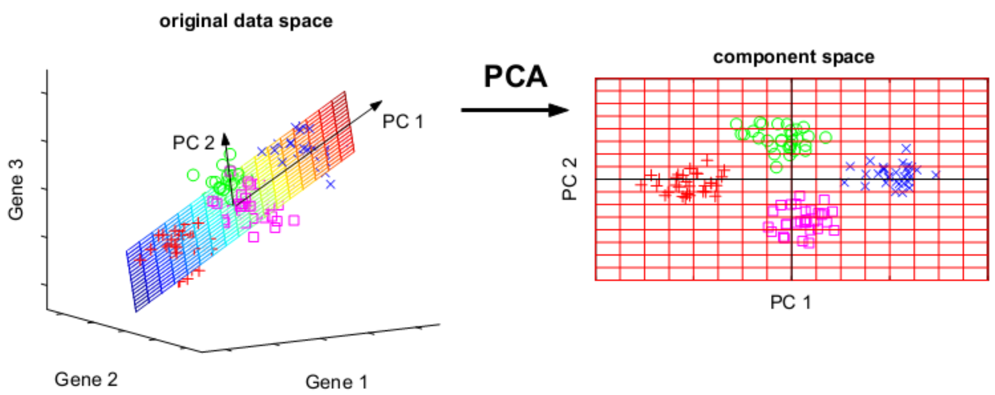

Figure 4: PCA demonstration [16]

This figure illustrated the transformation of PCA which reduces a large number of variables (genes) to a lower number of new variables termed principal components (PCs). Three-dimensional gene expression samples are projected onto a two dimensional component space that maintains the largest variance in the data. This two-dimensional visualisation of the samples allows making qualitative conclusions about the separability of our four experimental conditions[16].

A Gaussian Mixture Model is a parametric probability density function represented as a weighted sum of Gaussian component densities and is the next step of this algorithm for each of the three motion steps. This step is shown in the equation below.

$$p(x) = \sum_{k=1}^{K} \pi_k p(x|k)$$

$$p(x|k) = \frac{1}{\sqrt{2\pi}^d \sqrt{\det(C_k)}} e^{-\frac{1}{2}\left((x-\mu_k)^T C_k^{-1} (x-\mu_k)\right)}$$

With mean μ_k and covariance matrix C_k. The parameter estimation is performed by an expectation-maximization (EM) algorithm [5]. The EM algorithm is an efficient iterative procedure to compute the Maximum Likelihood (ML) estimate in the presence of missing or hidden data.

To show the functionality of the EM algorithm it is assign to the k-means algorithm which is more common. The k-means clusters the given data into k clusters in which each data point belongs to the cluster with the nearest mean [5]. The E-step would be the initialization of the beginning cluster centers and the M-step would be the according of the data to the nearest center.

After the EM steps three probability density functions are produced with five to ten Gaussians each. These functions are now used to calculate the likelihood of a state having to switch from one to another desired posture. The whole loop could now be computed as a maximum likelihood method.

$$x^*_{next} = argmax\, p_s(x)$$

For testing the machine learning algorithm some tests were performed doing the standup task before and after learning. When comparing the motion of the robot after the learning process and the motion performed by the robot initially, it becomes clear that through learning the motion gets smoother and, at the same time, appears more natural. The following figure shows the low-dimension trajectories of the robot before and after learning. It illustrates the success of the learning process, but also there is an oscillation around the point (0.5, -2) for the initial state, which might be caused by some inefficient motion steps of the robot.

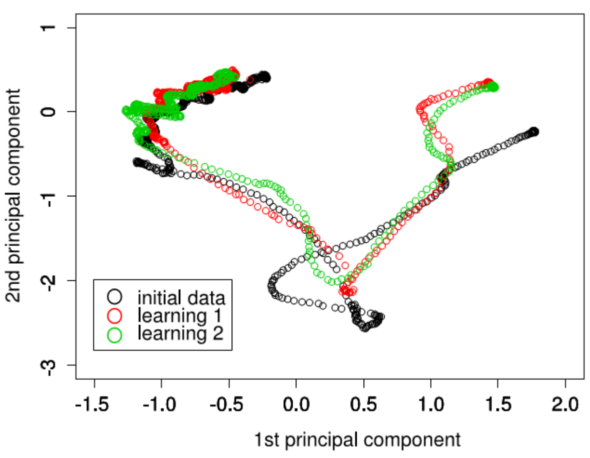

Figure 5: low-dimension posture trajectories [4]

To underline the successful results a posture changing norm *a(t)* was used. This is a Euclidian distance between the data of a time step *t* and *t-1* by using each joint angle as base.

$$a_{(t)} = \|x_t - x_{t-1}\|_2$$

The following figure shows the computed posture change norm for each time step. There are several peaks indicating a large change in the posture of the robot. After each learning iteration the amount of peaks decreases. This supports the hypothesis that the physical human robot interaction can be improved by using this machine learning algorithm.

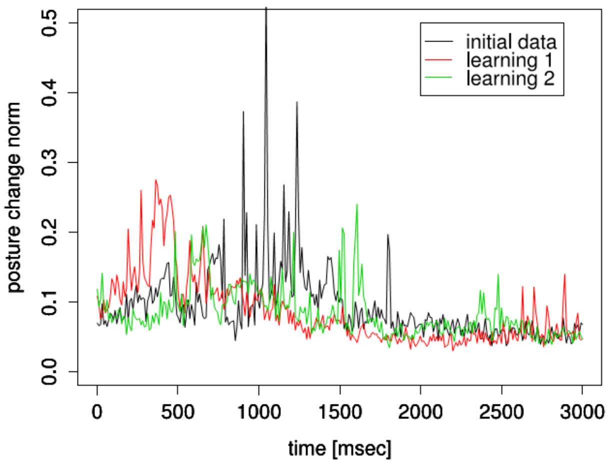

Figure 6: posture change norm

5 Conclusions and future work

In the main part of this paper I presented a simple machine learning algorithm to improve the behavior of the robot based on an evaluation by the human partner. Reducing the dimension leads to a decrease of the computational load and can be run online while the action is performed. In the task presented in this paper the robot is in close physical contact with his human partner and plays an active role in the performance of the common task. Through time measurement it is possible to show, that the robot´s performance was increased by using the learning algorithm.

Thus far the system is not using all the information that is given. It is focused on the switching rule. For more complex interactions it might be necessary to adapt to the set of desired postures or/and to feedback gains. Another limitation is the given feedback, that is only handled in the case of success.

In summary, the algorithms presented could increase the performance and lead to a successful interaction for simple tasks. To execute a more complex task, it is necessary to update the used algorithm by a method which is using feedback not only in a binary form.

A new interesting approach is presented in [6], by using a so called intention-driven dynamic model (IDDM). The Model is trained by observing the human behavior, additionally an approximate inference algorithm is used to infer the human´s intention. The results of that work are so good, that this approach could be the new state of the art algorithm and open many directions to go for future human robot interaction.

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