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(54) **Robot with automatic selection of task-specific representations for imitation learning**

Roboter mit automatischer Auswahl von aufgabenspezifischen Darstellungen zur Imitationserlernung

Robot doté d'une sélection automatique de représentations spécifiques de tâches pour apprentissage de l'imitation

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- **TOUSSAINT M ET AL: "Optimization of sequential attractor-based movement for compact behaviour generation" HUMANOID ROBOTS, 2007 7TH IEEE-RAS INTERNATIONAL CONFERENCE ON, IEEE, PISCATAWAY, NJ, USA, 29 November 2007 (2007-11-29), pages 122-129, XP031448832 ISBN: 978-1-4244-1861-9**

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Description

Field of invention

[0001] The invention generally relates to the field of autonomous robots. The invention also refers to a method to enhance the process of imitation learning with robots.

[0002] The invention provides a mechanism for the autonomous selection of suitable task-specific representations of movement-imitation data and therefore increases the autonomy of such systems. The autonomous selection can be driven by multiple integrated cues, such as statistical decision making, interaction with the teacher, but also model-based a priori knowledge.

[0003] "Imitation learning" is a term well understood by the skilled person in the field of autonomous robots. An introduction can be found in chapter 6.12 of Bekey "Autonomous robots", The MIT press, 2005.

Object of the invention

[0004] It is the object of the present invention to render more efficient a robot's imitation learning of a movement.

[0005] This object is achieved by means of the features of the independent claims. The dependent claims develop further the central idea of the present invention.

[0006] According to a first aspect the invention proposes a method for imitation-learning of movements of a robot, wherein the robot performs the following steps:

- observing a movement of an entity in the robot's environment,
- recording the observed movement using a sensorial data stream and representing the recorded movement in different task space representations,
- selecting a subset of the task space representations for the imitation learning and reproduction of the movement to be imitated.

[0007] The step of selecting a subset of the task space representations may use cues which the robot extracts from the sensorial data stream.

[0008] The step of selecting a subset of the task space representations may use the variance over multiple demonstrations of the movement, wherein task space representations in which the observations have the lowest inter-trial variance are chosen.

[0009] The step of selecting a subset of the task space representations may use attention-based methods.

[0010] The step of selecting a subset of the task space representations may use the kinematic or dynamic simulation of the human teacher.

[0011] Task elements for the selection step can be defined through discomfort, such as e.g. deviation from a default posture, and effort, such as e.g. based on the torque of effector joints, of the teacher during the task demonstration.

[0012] The task space selection may influence the movement reproduction process on the robot.

[0013] The invention also relates to a computer program product, executing a method as defined above when run on a computing device of a robot.

[0014] The invention furthermore relates to a robot, preferably a humanoid robot, having a computing unit designed to perform such a method.

[0015] The robot may be an industrial robot, which learns certain sequences of working steps by imitation learning.

[0016] Further advantages, objects and features of the invention will become evident for the skilled person when reading the following detailed description of preferred embodiments of the present invention when taken in conjunction with the only figure of the enclosed drawings.

Figure 1 shows a task space selection unit, which is part of a computing unit of a robot and

Figure 2 shows fitness values that represent the importance of the specific task space.

Detailed description of embodiments:

[0017] When a robot with a high number of degrees of freedom, such as a humanoid robot (see chapter 13 of *Bekey*), e.g. Honda's ASIMO robot, or an industrial robot, shall learn new movements by observing, recording and then imitating an entity in its environment (i.e. the space covered by e.g. visual sensor of the robot), such as e.g. a human teacher, a task-specific representation within so-called task spaces is proposed. The task-specific representation reduces the dimensionality of the data to learn, eases the correspondence problem and allows additional generalization.

[0018] The present invention provides mechanisms to autonomously (i.e. performed by a computing unit of the robot) select such task spaces by regarding multiple cues of different character.

[0019] The selection according to the invention is performed out of a plurality of task spaces which represent states of the robot and the environment in different coordinate systems.

[0020] "Cues" are selection criteria which the robot extracts from the sensorial input during a imitation-learning session.

[0021] With reference to Figure 1 now the imitation learning process together with an automatic task space selection unit will be explained. The task space selection unit is a logical unit in a computing unit of the robot.

[0022] The movement that shall be learned is demonstrated by a teacher or another entity in the robot's environment (e.g. other robots, animals, ...). The robot observes the demonstrated movement using sensor means, such as e.g. a video camera, which sensor means supply a data stream to the computing unit of the robot.

[0023] The data stream of the observed demonstrated movement is recorded as "Raw data" in data storage means which are connected to and accessed by the robot's computing unit.

[0024] E.g. motion capture or vision-based techniques, like color-tracking may be used for recording the observed demonstrated movement.

[0025] This "Raw data" is then projected into (i.e. represented in) different possible task spaces which are subsumed in the "Task space pool". The task space pool can be pre-set by programming or set up autonomously by the robot, e.g. in a preceding learning step.

[0026] Possible task space representations (coordinate systems) for e.g. a grasping task can be:

- absolute position of a robot's end effector,
- relative position of the robot's end effector wrt. the object that should be grasped,
- orientation of the robot's end effector, and
- if the robot is two-handed, also both hand positions may be controlled

[0027] Within known imitation learning approaches, either all of these task spaces are used to represent the learned task or a subset of them is chosen manually that fits best to the task. This manual intervention strongly limits the open-endedness and the interactive capabilities of the whole imitation learning framework.

[0028] With this invention in contrast, the "Task space selector" unit of the robot does this automatically. There are two ways how the task space selector unit influences the imitation learning process:

First (1), a subset of task space representations are selected from the "Task space pool" and all other task spaces are discarded. The selection can be carried e.g. based on selection criteria (called "cues" in the following") preferably extracted from the sensorial data stream. Therefore only actually useful (as expressed by the selection criteria) task spaces are represented and later reproduced by the robot, while the remaining task spaces can be discarded.

[0029] Once a movement to be imitated has been learned, preferably an optimization method is applied on the different task space representations in order to efficiently (in terms of the robot's constraints) reproduce the learned movement. Hence, second (2), the "Task space selector" unit can influence the "Reproduction" of the movement with the help of fitness values. The fitness is a weighted combination of what the different cues "believe" to be important, therefore, fitness can be based e.g. on:

○ inter-trial variance
○ discomfort
○ joint torque
○ attention signal

[0030] Before the robot is able to reproduce a learned movement, this movement can be optimized wrt. different criteria. These criteria may be e.g. self-collision avoidance, avoiding the joint limits, holding balance or fulfilling additional tasks such as always gazing at a specific position while performing the movement. This optimization can be performed e.g. using an evolutionary algorithm, wherein a fitness function ("cost function") assesses the quality ("fitness") of different movements in terms of e.g. these criteria and outputs corresponding fitness values.

[0031] Based on the information from the different cues, the task space selector generates fitness values for all task spaces that are used for the movement representation over all timesteps of the movement. Example (see figure 2): A gesture should be learned that involves the right hand during the first part of the movement and the left hand during the second part only. For this, maybe two task spaces are chosen for the representation, one for the left hands position and one for the right. For both of these task spaces, the task space selector generates fitness values that represent the importance of the specific task space. The movement optimization uses these fitness values to blend both task representations in order to produce a correct outcome.

[0032] During the reproduction, task spaces may be blended based on e.g. importance criteria, i.e. not only a single representation but a weighted blend of task space can be used. Different task space representations can be used sequentially when carrying out a learned movement.

[0033] The cues that are involved within the "Task space selector" unit can have very different characteristics, such as:

- A variance-based measure that assigns a high importance of a specific task space if the inter-trial variance over several task demonstrations is low. In [2], the basic idea of using the variance as an importance measure was successfully evaluated. As to this aspect, the disclosure of [2] is incorporated herewith by reference.
- An interactive cue that incorporates information about the teacher's behavior. Importance is defined through explicit attention generation by the teacher. In [3], experiments in the domain of parent-infant research, show such attention mechanisms for defining importance. As to this aspect, the disclosure of [3] is incorporated herewith by reference.
- A kinematic or dynamic simulation of a human model that is used to analyze the discomfort and effort of the human demonstrator. Uncomfortable postures that the human went through are likely to be important for the task. Prior art [4] uses similar cost functions for predicting human postures, instead of analyzing them with the goal of defining task importance for imitation. As to this aspect, the disclosure of [4] is incorporated herewith by reference.

Example 1: Task spaces for moving objects

[0034] In this example the robot shall learn to put an object (e.g. a ball) into a basket. For this, a human teacher shows the robot a set of demonstrations how to perform the task in situations with different starting positions for ball and basket. Possible task spaces in the "Task space pool" are:

- absolute position of the ball,
- absolute position of the basket,
- relative position of the ball wrt. the basket
- additional task spaces because of maybe other objects in scene (e.g. position of the ball wrt. any other recognized object)

[0035] In this example, two elements of the "Task space selector" are used in order to automatically determine the task spaces that should be used for representing the task.

[0036] First, the interactive cue signalizes that the important object that should be moved is the ball. This results from the teacher actively shaking the object to generate attention. It already limits the set of task spaces strictly to only those that are related to the ball.

[0037] Next, the statistical evaluation can decide further which of these ball-related task spaces are important, because the teacher demonstrates the task several times under different conditions. The idea of the statistical evaluation is that important aspects of a task have a low inter-trial variance over multiple demonstrations. This also applies to this example, because the evaluation will show that the use of the absolute position of the ball is very variant. However, the position of the ball in relation to the basket will be less variant and would result in a better representation.

[0038] The "Task space selector" decides on using the relative position of ball and basket as the "Selected task space" and directly influences the "Representation".

[0039] In cases where the decision between different task spaces is not easy, the "Task space selector" may also decide to represent more than one. Then, by using the fitness values (e.g. variance information from the statistical evaluation, attention signal from the interactive cue), these task spaces can be blended or deactivated during the movement reproduction.

Example 2: Task spaces for gestures

[0040] This example explains the use of a kinematic simulation of a human model for deciding on task-relevant movements of distinct body parts. A humanoid robot shall learn to reproduce gestures with either one or both arms. Therefore, the main question in this example is which arm is involved in the gesture to learn. Using a statistical evaluation only, like in the previous example, is not enough to answer this question. This is because if the movement is performed with one arm, the other arm will remain still. This would result in low inter-trial variance over multiple demonstrations. However, the stillness of the uninvolved arm shouldn't be part of the representation. On the other hand, holding an arm still doesn't necessarily mean that it is unimportant.

[0041] To overcome those problems a model-based cue is used within the "Task space selector". The observed motion of the human teacher is mapped onto a human model within a kinematic simulation. Based on this model, different cost functions are evaluated. An effort value for each arm is calculated that is based on the torque of all arm joints. And the discomfort is estimated, which increases if the deviation of the human's posture from its idle position gets larger.

[0042] Using these two measures, the "Task space selector" is able to robustly decide on which arm is involved in the demonstrated gesture and to choose the representation accordingly.

[1] M. Toussaint, M. Gienger and C. Goerick, "Optimization of sequential attractor-based movement for compact behaviour generation" 7th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2007), 2007

[2] M. Mühlig, "Task learning of bimanual object handling", diploma thesis, 2008

[3] Y. Nagai and K. J. Rohlfing, "Parental Action Modification Highlighting the Goal versus the Means", in Proceedings of the IEEE 7th International Conference on Development and Learning (ICDL'08), August 2008.

[4] K. Abdel-Malek, J. Yang, Z. Mi, V. Patel and K. Nebel, "Human Upper Body Motion Prediction", Applied Simulation and Modelling, 2004

[5] EP - A2 -1 537 959, Abb Research Ltd., " A method and a system for programming an industrial robot" discloses a method of learning by demonstration for programming a robot with a visual feedback to the operator of the point presently taught to the robot.

Effector	The part of the robot that is being controlled. This can e.g. be the hand or the head
Task vector	A vector that comprises the variables that are controlled. For a humanoid robot, this can e. g. be the hand position or the gaze direction of the head.
Degrees of freedom	The degrees of freedom are a minimal set of coordinates that allow the system to move. They can be controllable (like driven joints of a robot) or uncontrollable.
Configuration space	Space spanned by the degrees of freedom
Joint space	This term is often used in robotics and means *configuration space*
Task space	The space that is described by the task vector. If e. g. the hand position of a robot in x-, y- and z-direction is controlled, the task space has the dimension 3 and is spanned by these coordinates.

Claims

1. A method for imitation-learning of movements of a robot, wherein the robot performs the following steps:

- observing a movement of an entity in the robot's environment,
- recording the observed movement using a sensorial data stream and representing the recorded movement in different task space representations,
- selecting a subset of the task space representations for the imitation learning and reproduction of the movement to be imitated, the subset comprising one task space representation or a sequence of different task space representations for the reproduction of the movement.

2. The method according to claim 1,
wherein the step of selecting a subset of the task space representations uses cues which the robot extracts from the sensorial data stream

3. The method according to claim 2,
wherein the step of selecting a subset of the task space representations uses the variance over multiple demon-

strations of the movement, wherein task space representations in which the observations have the lowest inter-trial variance are chosen.

4. The method according to claim 2 or 3,
wherein the step of selecting a subset of the task space representations uses attention-based mechanisms.

5. The method according to any of claims 2 to 4,
wherein the step of selecting a subset of the task space representations uses the kinematic or dynamic simulation of the human teacher.

6. The method according to claim 5,
wherein task elements for the selection step are defined through discomfort, such as e.g. deviation from a default posture, and effort, such as e.g. based on the torque of effector joints, of the teacher during the task demonstration.

7. The method according to any of the preceding claims,
wherein the task space selection influences the movement reproduction process on the robot.

8. The method according to any of the preceding claims,
wherein an optimization method is applied on the different task space representations in order to efficiently reproduce the movement.

9. The method according to any of the preceding claims, wherein different task space representations are used time-sequentially when reproducing a learned movement.

10. A computer program product,
executing a method according to any of the preceding claims when run on a computing device of a robot.

11. A robot, preferably a humanoid robot, having a computing unit designed to perform a method according to any of claims 1 to 9.

12. The robot of claim 11,
wherein the robot is an industrial robot, which learns certain sequences of working steps by imitation learning.

Patentansprüche

1. Verfahren zum Erlernen von Bewegungen eines Roboters durch Imitieren, wobei der Roboter die folgenden Schritte durchführt:

- Beobachten einer Bewegung einer Funktionseinheit in der Umgebung des Roboters,
- Aufzeichnen der beobachteten Bewegung unter Verwendung eines sensorischen Datenstroms und Darstellen der aufgezeichneten Bewegung in unterschiedlichen Aufgabenraumdarstellungen,
- Auswählen einer Teilmenge der Aufgabenraumdarstellungen zur Imitationserlernung und Wiedergabe der zu imitierenden Bewegung, wobei die Teilmenge eine Aufgabenraumdarstellung oder eine Folge von verschiedenen Aufgabenraumdarstellungen für die Wiedergabe der Bewegung aufweist.

2. Verfahren gemäß Anspruch 1,
wobei der Schritt des Auswählens einer Teilmenge der Aufgabenraumdarstellungen Hinweise verwendet, die der Roboter aus dem sensorischen Datenstrom extrahiert.

3. Verfahren gemäß Anspruch 2,
wobei der Schritt des Auswählens einer Teilmenge der Aufgabenraumdarstellungen die Streuung über mehrere Vorführungen der Bewegung verwendet, wobei die Aufgabenraumdarstellungen, in denen die Beobachtungen, die die geringste Streuung zwischen den Versuchen haben, verwendet werden.

4. Verfahren gemäß Anspruch 2 oder 3,
wobei der Schritt des Auswählens einer Teilmenge der Aufgabenraumdarstellungen aufmerksamkeitsbasierte Mechanismen verwendet.

5. Verfahren gemäß einem der Ansprüche 2 bis 4,
wobei der Schritt des Auswählens einer Teilmenge der Aufgabenraumdarstellungen kinematische oder dynamische Simulation des menschlichen Lehrers verwendet.

6. Verfahren gemäß Anspruch 5,
wobei die Aufgabenelemente für den Auswahlschritt durch Unannehmlichkeiten, wie z.B. die Abweichung von einer Vorgabehaltung, und Anstrengung, wie z.B. basierend auf dem Drehmoment von Effektorgelenken, des Lehrers während der Aufgabenvorführung definiert werden.

7. Verfahren gemäß einem der vorhergehenden Ansprüche, wobei die Aufgabenraumauswahl das Bewegungswiedergabeverfahren des Roboters beeinflusst.

8. Verfahren gemäß einem der vorhergehenden Ansprüche, wobei ein Optimierungsverfahren auf die verschiedenen Aufgabenraumdarstellungen angewendet wird, um die Bewegung wirkungsvoll wiederzugeben.

9. Verfahren gemäß einem der vorhergehenden Ansprüche, wobei verschiedene Aufgabenraumdarstellungen zeitlich aufeinanderfolgend verwendet werden, wenn eine erlernte Bewegung wiedergegeben wird.

10. Computerprogrammprodukt,
das ein Verfahren gemäß einem der vorhergehenden Ansprüche ausführt, wenn es auf einer Berechnungsvorrichtung eines Roboters laufen gelassen wird.

11. Roboter, vorzugsweise ein menschenähnlicher Roboter, mit einer Recheneinheit, die konzipiert ist, um ein Verfahren gemäß einem der Ansprüche 1 bis 9 durchzuführen.

12. Roboter gemäß Anspruch 11,
wobei der Roboter ein Industrieroboter ist, der gewisse Abfolgen von Arbeitsschritten durch Imitationserlernen erlernt.

Revendications

1. Procédé pour apprentissage par imitation de mouvements d'un robot, dans lequel le robot exécute les étapes suivantes :

   - observation d'un mouvement d'une entité située dans l'environnement du robot,
   - enregistrement du mouvement observé en utilisant un flot de données sensorielles et représentation du mouvement enregistré dans différentes représentations de l'espace opérationnel,
   - sélection d'un sous-ensemble des représentations de l'espace opérationnel pour l'apprentissage par imitation et reproduction du mouvement à imiter, le sous-ensemble comprenant une représentation de l'espace opérationnel ou une séquence de différentes représentations de l'espace opérationnel pour la reproduction du mouvement.

2. Procédé selon la revendication 1, dans lequel l'étape de sélection d'un sous-ensemble des représentations de l'espace opérationnel utilise des repères que le robot extrait du flot de données sensorielles.

3. Procédé selon la revendication 2, dans lequel l'étape de sélection d'un sous-ensemble des représentations de l'espace opérationnel utilise la variance sur de multiples démonstrations du mouvement, dans lequel des représentations de l'espace opérationnel dans lequel les observations ayant la variance inter-essai la plus basse sont choisies.

4. Procédé selon les revendications 2 ou 3, dans lequel l'étape de sélection d'un sous-ensemble des représentations de l'espace opérationnel utilise des mécanismes basés sur l'attention.

5. Procédé selon l'une quelconque des représentations 2 à 4, dans lequel l'étape de sélection d'un sous-ensemble des représentations de l'espace opérationnel utilise la simulation cinématique ou dynamique de l'enseignant humain.

6. Procédé selon la revendication 5, dans lequel des éléments de travail pour l'étape de sélection sont définis par inconfort, tel que par exemple la déviation depuis une posture par défaut, et effort, tel que par exemple basé sur le

couple des joints du terminal, de l'enseignant pendant la démonstration de la tâche.

7. Procédé selon l'une quelconque des revendications précédentes, dans lequel la sélection de l'espace opérationnel influence le processus de reproduction du mouvement sur le robot.

8. Procédé selon l'une quelconque des revendications précédentes, dans lequel un procédé d'optimisation est appliqué sur les différentes représentations de l'espace opérationnel afin de reproduire efficacement le mouvement.

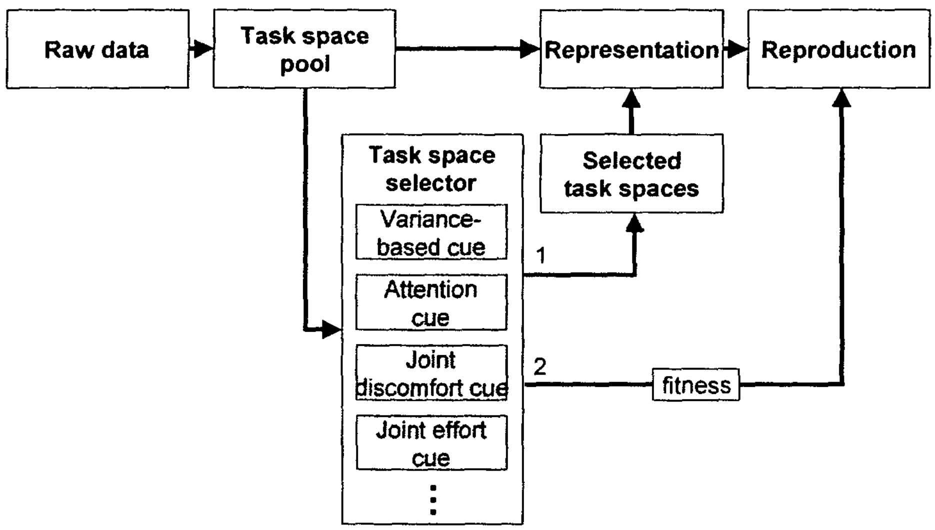
9. Procédé selon l'une quelconque des revendications précédentes, dans lequel différentes représentations de l'espace opérationnel sont utilisées séquentiellement dans le temps lors de la reproduction d'un mouvement appris.

10. Produit programme d'ordinateur, exécutant un procédé selon l'une quelconque des revendications précédentes lorsqu'il fonctionne sur un dispositif de calcul d'un robot.

11. Robot, de préférence robot humanoïde, ayant une unité de calcul conçue pour exécuter un procédé selon l'une quelconque des revendications 1 à 9.

12. Robot selon la revendication 11, dans lequel le robot est un robot industriel qui apprend certaines séquences d'étapes de travail par apprentissage par imitation.

Figure 1


Raw data
Task space pool
Representation
Reproduction
Task space selector
Variance-based cue
Attention cue
Joint discomfort cue
Joint effort cue
Selected task spaces
1
2
fitness

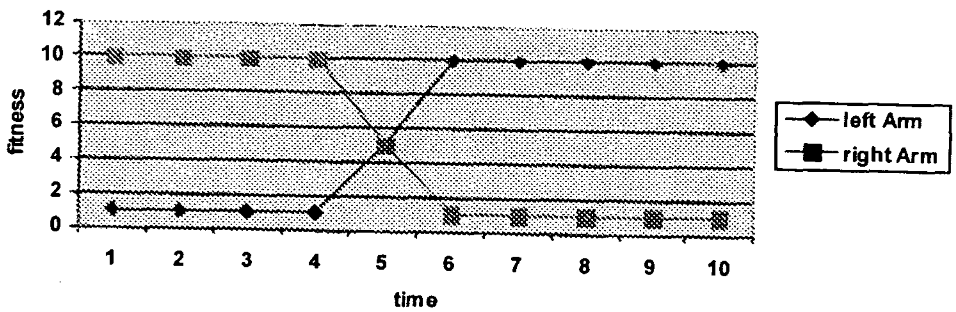


Fig ure 2

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- EP 1537959 A2 **[0043]**

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- **Bekey.** Autonomous robots. The MIT press, 2005 **[0003]**
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