Artificial Intelligence in Medicine 74 (2016) 32–43

Contents lists available at ScienceDirect

Artificial Intelligence in Medicine

journal homepage: www.elsevier.com/locate/aiim

Gesteme-free context-aware adaptation of robot behavior in human–robot cooperation

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ARTICLE INFO

Article history:
Received 19 March 2016
Received in revised form 22 October 2016
Accepted 25 October 2016

Keywords:
Activity recognition
Cooperative robotics
Context-awareness

ABSTRACT

Background: Cooperative robotics is receiving greater acceptance because the typical advantages provided by manipulators are combined with an intuitive usage. In particular, hands-on robotics may benefit from the adaptation of the assistant behavior with respect to the activity currently performed by the user. A fast and reliable classification of human activities is required, as well as strategies to smoothly modify the control of the manipulator. In this scenario, gesteme-based motion classification is inadequate because it needs the observation of a wide signal percentage and the definition of a rich vocabulary.
Objective: In this work, a system able to recognize the user's current activity without a vocabulary of gestemes, and to accordingly adapt the manipulator's dynamic behavior is presented.
Methods and material: An underlying stochastic model fits variations in the user's guidance forces and the resulting trajectories of the manipulator's end-effector with a set of Gaussian distribution. The high-level switching between these distributions is captured with hidden Markov models. The dynamic of the KUKA light-weight robot, a torque-controlled manipulator, is modified with respect to the classified activity using sigmoidal-shaped functions. The presented system is validated over a pool of 12 näive users in a scenario that addresses surgical targeting tasks on soft tissue. The robot's assistance is adapted in order to obtain a stiff behavior during activities that require critical accuracy constraint, and higher compliance during wide movements. Both the ability to provide the correct classification at each moment (sample accuracy) and the capability of correctly identify the correct sequence of activity (sequence accuracy) were evaluated.
Results: The proposed classifier is fast and accurate in all the experiments conducted (80% sample accuracy after the observation of ~450 ms of signal). Moreover, the ability of recognize the correct sequence of activities, without unwanted transitions is guaranteed (sequence accuracy ~90% when computed far away from user desired transitions). Finally, the proposed activity-based adaptation of the robot's dynamic does not lead to a not smooth behavior (high smoothness, i.e. normalized jerk score <0.01).
Conclusion: The provided system is able to dynamic assist the operator during cooperation in the presented scenario.

1. Introduction

Cooperatively controlled robotic assistants are receiving greater acceptance in several application domains (e.g. industrial, medical) because of the advantages coming from the human agent involved in the control loop [1]. In hands-on robotic surgery, the surgeon moves tools fixed to the manipulator's end-effector by direct application of forces on the robot's links [2], achieving increased accuracy and safety during the operations, e.g. in retinal surgery [3] and orthopedic surgery [4]. Thus, hands-on controlled robots take advantage of the human decision making process and experience combining safety and intuitiveness with the enhancement strategies provided by the robot (e.g. hand tremor rejection or fatigue reduction) [5]. In assistive and rehabilitation robotics, for instance, the use of a manipulator proved to enhance post-trauma therapies [6]. The human user is often tightly coupled to the robotic device [6] and the use of the manipulator could provide active patient assistance in task-specific arm movement completion [7,8] or guidance for a paretic arm during particular constrained movements [9]. In particular, the cooperative control approach in rehabilitation was proven to enable patients to train in an active, variable and more natural way, with more physiological muscle activity [10].

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http://dx.doi.org/10.1016/j.artmed.2016.10.001
0933-3657/

To know *how* and *when* to provide the most appropriate level of assistance (e.g. in terms of adaptation of control strategy) is advisable in order to provide a more versatile robotic assistant and to get the best performances from the shared human–robot cooperation [11–13]. For example, during surgical brain cortex mapping procedures, the manipulator compliance can be adapted in order to damp the tool motion near the patient while maintaining highly compliant behavior elsewhere [14]. Conversely, in robot-aided gait rehabilitation, the robot assistance can be modified on the basis of the patient influence on the control, e.g. trigger leg movement whether a relevant muscle activity is detected [10].

In order to select the most suitable assistance at each moment it is necessary to infer the user's current activity/intention from raw input signals, online and in real-time [15]. In fact, effective human–robot interaction should avoid explicit UI mechanisms to change the assistant behavior [16]. Thus, a robot should be able to recognize the user's non-verbal cues [17], involving a degree of awareness of its surrounding [16].

Machine-learning algorithms are exploited in the field of assistive robotics to provide intuitive control of prosthesis (e.g. to predict switching between multiple functions of a powered artificial limb [6]) or to infer the user's intention of motion (e.g. to coordinate walking support exoskeletons for paraplegia patients [18]). They have also shown potential application in pre-surgical analysis, in order to classify different types of epilepsy in a fully automatic way [19].

In robotic surgery applications, intention-awareness has been addressed in order to distinguish whether a specific action, e.g. the violation of an active constraint [1], is intentionally performed, thus modifying the manipulator behavior when the action is intended, e.g. allowing the user violation [20]. Conversely, during surgical targeting tasks, activity recognition and online segmentation of the procedures into simple subtasks could allow to modify the modulation of the robot compliance with respect to the currently performed activity [12,21].

A well-known approach to activity recognition is based on hidden Markov models (HMMs) [22]. HMMs are double-stochastic generative processes in which the observable output data is considered to be produced by a random variable taking values in a finite state space. Because of the very rich model's mathematical structure, HMMs are successfully applied to speech recognition [22], handwriting [23], gesture recognition [24,25] as well as motion classification [26–28].

Based on the assumption that human motion actions can be split into a set of primitives (called *gestemes* [12]), high-level complex activities are considered to be produced by a temporal sequence of those primitives. The need to provide a complete set of gestemes have pointed out limitations in this approach, leading to an offline segmentation of performed tasks [12]. Furthermore, attempts to perform online classification were proved to be reliable (i.e. accuracy of ∼80%) only when observing a large percentage of the signal, i.e. more than 60% [29]. Finally, once a fast and robust recognition of the current surgeon's activity is provided, a robotic system able to adapt its behavior to the user's intention should include a strategy to smoothly switch among different control modalities [30].

In this work recognition of surgeon's activities during hands-on robotic surgery is aimed, to accordingly adapt the manipulator's behavior in order to augment the safety and intuitiveness of the cooperation. An online algorithm is presented, able to provide a robust and real-time recognition of surgeon's activities without the need to define gestemes. The underlying stochastic model [31,32] fits the increments in the user's guidance forces and the resulting trajectory of the manipulator with the components of a Gaussian mixture model (GMM). The high-level switching between the different components is captured using a set of continuous HMMs, one for each activity. This is a more structured approach with respect, e.g. to a black-box approach based on deep feedforward and recurrent neural networks to model processes with unknown states number and information length in time. Furthermore recurrent neural networks stability is not granted.

The provided classification is then exploited to trigger different dynamic behaviors of a torque-controlled manipulator. A strategy to switch among different behaviors is also presented, that modulates the robot stiffness and damping according to the user's activity.

The remainder of the paper is structured as follows. In Section 2, first the stochastic model used to describe user's actions is described, then the classification algorithm used to discriminate online among the activities is presented. In Section 3, the scenario and the selected modeled activities are described together with a strategy to smoothly modify the control of the assistant manipulator. Experimental evaluation of both the classifier and the adaptive robot control is presented in Section 4, encompassing a validation protocol over a pool of twelve näive users. Finally, results are presented in Section 5 and discussed in Section 6.

2. Recognition of surgeon's activity

2.1. Activity model

Surgeon's activity during hands-on robotic surgery can be described by human Cartesian driving forces ($\mathbf{f}$) and resulting manipulator's Cartesian end-effector trajectory ($\mathbf{x}$), expressed as vectors of n-samples over time ($t = 1, \ldots, n$), i.e. $\mathbf{f} = (\mathbf{f}^1, \ldots, \mathbf{f}^n)$ and $\mathbf{x} = (\mathbf{x}^1, \ldots, \mathbf{x}^n)$. Both $\mathbf{f}$ and $\mathbf{x}$ are dependent on the current activity, thus they can be combined in a sequence of n 6-dimensional vectors $\mathbf{d}^t$ [31], i.e.

$$\mathbf{d} = (\mathbf{d}^1, \ldots, \mathbf{d}^n) = \begin{pmatrix} \mathbf{x} \\ \mathbf{f} \end{pmatrix}^T \tag{1}$$

that describes the user's action on the manipulator during cooperation.

The vector $\mathbf{d}$ can be expressed by a sequence of increments with respect to the current user's action [32], i.e.

$$\mathbf{d}^t = \mathbf{d}^{t-1} + \Delta\mathbf{d}^t. \tag{2}$$

Vector $\Delta\mathbf{d}^t$ represents the increment at time t and is modeled as

$$\Delta\mathbf{d}^t = \mathbf{T}_{z_t} + \sqrt{\mathbf{C}_{z_t}} \cdot \mathbf{w}^t \tag{3}$$

thus being the emission of a 6-dimensional Gaussian distribution (*low-level* model) labeled $z_t \in \{1, \ldots, M\}$ with $\mathbf{T}_{z_t}$ mean and $\mathbf{C}_{z_t}$ covariance. Vector $\mathbf{w}^t$ is the sample of a zero-mean and identity covariance Gaussian random vector. Eq. (2) is a switched-dynamical system of type $(d/dt)q^t = f_{z_t}(t)$, [33], with $f_{z_t} \equiv \Delta\mathbf{d}^t$ and Δt considered unitary, thus it is fully characterized by M Gaussian distributions defined by the $\mathbf{T} = (\mathbf{T}_1, \ldots, \mathbf{T}_M)$ and $\mathbf{C} = (\mathbf{C}_1, \ldots, \mathbf{C}_M)$ matrices, one at the time producing the current increment $\Delta\mathbf{d}^t$.

At higher-level, the temporal sequence of low-level models $\mathbf{z} = (z_1, \ldots, z_n)$ is considered as the sample of a Markov chain (*high-level* model) in which each state represents one of the M *low-level* models. Thus, each activity $a \in \{1, \ldots, A\}$ is characterized by one M-states continuous HMM $\lambda_a = \{\pi_a, \mathbf{B}_a, \mathbf{T}, \mathbf{C}\}$ in which the state emission probability density parameters are in fact the $\mathbf{T}$ and $\mathbf{C}$ matrices, π_a represents the prior probability of each state of the HMM and $\mathbf{B}_a$ is the transition matrix that characterize the *low-level* models switching for the activity a, i.e. $p(\mathbf{z}|a) = p(\mathbf{z}|\mathbf{B}_a, \pi_a)$.

This two-level hierarchical stochastic model is described in Fig. 1.