Journal of Manufacturing Systems 44 (2017) 287–294

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

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

Human motion prediction for human-robot collaboration☆

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ARTICLE INFO

Article history:
Received 12 November 2015
Received in revised form 9 February 2017
Accepted 3 March 2017
Available online 13 May 2017

Keywords:
Human-robot collaboration
Human motion prediction
Assembly

ABSTRACT

In human-robot collaborative manufacturing, industrial robots would work alongside human workers who jointly perform the assigned tasks seamlessly. A human-robot collaborative manufacturing system is more customised and flexible than conventional manufacturing systems. In the area of assembly, a practical human-robot collaborative assembly system should be able to predict a human worker's intention and assist human during assembly operations. In response to the requirement, this research proposes a new human-robot collaborative system design. The primary focus of the paper is to model product assembly tasks as a sequence of human motions. Existing human motion recognition techniques are applied to recognise the human motions. Hidden Markov model is used in the motion sequence to generate a motion transition probability matrix. Based on the result, human motion prediction becomes possible. The predicted human motions are evaluated and applied in task-level human-robot collaborative assembly.

1. Introduction

Industrial robots have been widely used in modern manufacturing systems. In the future, the industrial robots may share the same working environment with human workers. An industrial robot can provide better fatigue, higher speed, and greater strength and accuracy. A human worker, on the other hand, possesses better adaptability and sensorimotor capabilities. The concept of human-robot collaboration (HRC) combines in essence the advantages of both the industrial robots and the human workers. In an HRC system, human workers and industrial robots team up and work jointly on the same shared tasks. An essential requirement for such an HRC system is human safety [1,2]. Traditionally, by giving different instructions to the humans and the robots, time separation and space separation approaches have been common [3]. To ensure safe HRC, both humans and robots need to follow specific work instruction sheets strictly. According to the instructions, certain human worker's motions are predictable. However, to support and collaborate with a human worker at the task level, an industrial robot needs to work alongside the (coexisting) human worker [4].

Recently, much work has focused on HRC safety [1,2,5]. However, safety is only the first step towards a practical HRC manufacturing system. An HRC manufacturing system is more customised and flexible than conventional manufacturing systems. An efficient HRC system should be able to understand a human worker's intention and assist the human during an assembly task. Since a human worker's (work-related) motions are limited and repetitive, the authors have modelled an assembly task as a sequence of human motions. Existing human motion recognition techniques can be applied to recognise the human motions associated with the assembly task. The recognised human motions are modelled by Hidden Markov model (HMM). The motion transition and observation probability matrices are then generated after solving the HMM. Based on the result, human motion prediction becomes possible. The human intention is analysed with the input of predicted human motion. The predicted human intention can be used as input for assistive robot motion planning. The industrial robot can thus be controlled to support and collaborate with the human worker based on the planned robot motions. The workflow of human motion prediction in HRC is shown in Fig. 1.

The remainder of this paper is organised as follows. Section 2 reviews previous work in the area of human motion prediction. Section 3 discusses the problem formulation and representation. Section 4 introduces the HMM process in the human motion recognition context. Section 5 reports a car engine assembly test case to validate the presented concept. Section 6 discusses the result of the car engine assembly test case. Section 7 summarises the paper with future works and conclusions.

☆ Peer-review under responsibility of the Scientific Committee of NAMRI/SME.

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http://dx.doi.org/10.1016/j.jmsy.2017.04.009
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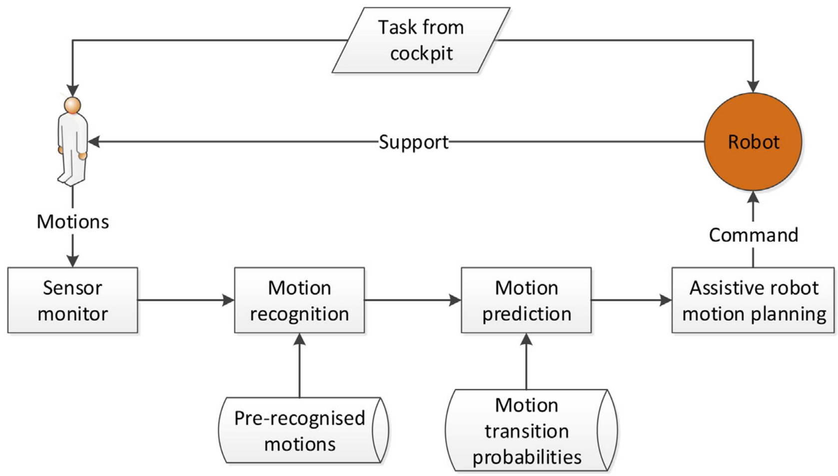


Fig. 1. Workflow of human motion prediction in HRC.

2. Related work

Human motion estimation and prediction can be analysed from different perspectives. Neuroscience researchers analysed human motions and behaviours through human brain neural network structures [6]. The human brain is a highly flexible computational system. Since a person has a limited amount of energy and resources, the possible future motions are always analysed by our brain before execution. It can predict the future outcomes of actions and change them when they are unlikely to achieve the expected results. Horowitz et al. [7] provided a feedback mathematical filter that determines human arm reaching intention. The proposed mathematical filter estimates and displays a human worker's underlying intended trajectory in real-time. The mathematical filter combines a human arm model with the force data collected from the human arm to determine the human worker's underlying intended reaching position. Their another paper [8] proved that the human motion is predictable even if the motion is only partially performed. The neuroscience researchers confirmed the hypothesis that human motion is predictable to a certain extent. These research efforts have established a theoretical foundation for human motion prediction in HRC applications.

Researchers in the field of computer vision are also interested in human motion estimation and prediction. Reddy et al. [9] explained a novel human motion estimation framework called feature-tree. The feature-tree framework utilised K-Nearest Neighbours (KNN) in features retrieval. Their system provided a simple solution for practical and incremental motion estimation problems. Lu et al. [10] introduced an HMM-based hand motion estimation system. The system utilised two levels of HMM. The hand detection features were abstracted by the Histogram of Oriented Gradient (HOG) algorithm first. The abstracted features were then sent to the HMM algorithm for hand motion classification and prediction. Feng et al. [11] combined the HOG and the Support Vector Machine (SVM) algorithm for static hand motion estimation. The HOG features are utilised in the SVM training process. The trained SVM classifier is used for motion prediction. Hasan et al. [12] introduced a hand motion estimation system. Several hand motions were predefined in the system. The system enabled a multi-layer artificial neural network (ANN) which applies a back-propagation learning algorithm. Li and Fu [13] introduced a general framework for human activity prediction. They compared their approach with HMM, SVM, and KNN based methods. Advantages and disadvantages of different approaches were discussed. Ryoo [14] presented a dynamic bag-of-words method for human motion prediction in streaming videos. The human motions were represented as an integral histogram of spatio-temporal features. Ding et al. [15] provided a human motion prediction approach in video sequences. Spatio-temporal patterns were modelled by a Hierarchical Self-Organising Map (HSOM). The continuous human motions were predicted by Variable order Markov Model (VMM). These researchers provided solutions for general human motion prediction problems. The applicability of the proposed solutions in the HRC field still needs to be carefully examined.

Some of the researchers in the HRC field also investigated into human motion estimation and prediction. Mainprice et al. [16] claimed that the single-arm reaching motion is an optimal trajectory with an unknown function. Human also provides the capability to adapt trajectory according to a collaborator's motion. The trajectory optimiser Stochastic Trajectory Optimisation for Motion Planning (STOMP) was applied to predict human motion [17]. The result of the paper shows that the predicted human motion in the robot's motion planner can increase interaction safety and efficiency between the human worker and the robot. Another paper from the same author presented a framework that can predict a human's motion early by using Gaussians Mixture Model (GMM) algorithm [18]. The predicted human motion is used as information support for HRC. Bascetta et al. [19] utilised visual tracking and human motion estimation for safe human-robot interaction cell design. Colour based model and the GMM algorithm were applied to the human detection task. The detected human is tracked by a partial filter. The human motion estimation problem was solved by the HMM algorithm. Li and Ge [20] introduced a human intention estimation method by using neural network technology. The estimated human motion was integrated into an adaptive impedance control. The proposed method enabled the robot to collaborate with its human partner actively. In a paper by Hawkins et al. [21], an HRC human motion prediction system was implemented. A Bayes Network modelled the assembly task structure. Another research [22] predicted human intention in medical applications. The human intention was predicted by the SVM algorithm.

In the HRC field, many researchers attempted to design coexisting HRC systems. Coupeté et al. [23] introduced an HRC system that helps human worker gesturally control an industrial robot in an assembly line. The acceptability of an operator to work with a robot on collaborative task was evaluated. Gesture recognition was applied to enable a natural collaboration between a human worker and a robot. Rozo et al. [24] demonstrated that a robot could learn movement from a human through programming by demonstration approach. The described motion was segmented into different stages. Various stages were modelled by an adaptive duration hidden semi-Markov model (ADHSMM). Fiore et al. [25] developed

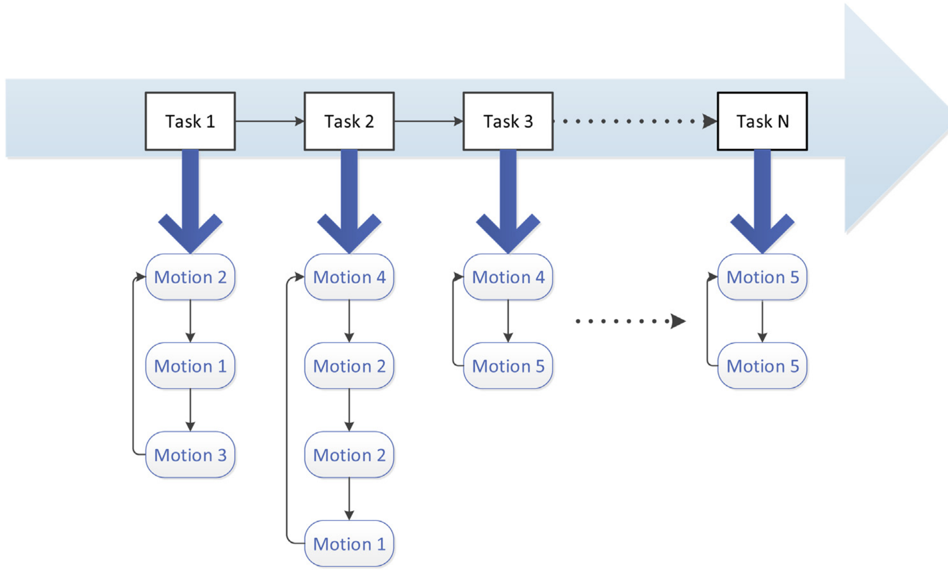


Fig. 2. Example of task-level representation in an assembly station.

an HRC supervision system that can be executed in a flexible way. The link between robot motions and the real world was established through a knowledge-based motion planner. Another research [26] formulated and designed the HRC process by finite state automata (FSA). One HRC task was defined as a collection of different stages. With the collaboration mode pre-defined for each stage, the HRC system was created. Moreover, Müller et al. [27] proposed a general HRC system for an automotive assembly line. In their paper, high-level system planning and integration were discussed.

Despite the achievements in the literature [28], the behaviours between humans and robots in an HRC system are still unclear as far as human motion and intention are concerned.

3. Problem formulation

The authors of this paper intend to model a product assembly task as a sequence of human motions. In this section, the problem discussed in the paper is formulated. Task-level assembly and motion recognition is introduced. Based on formulated problem and analysis, statistic model solution is selected.

3.1. Task-level assembly

In modern manufacturing systems, operator instruction sheet (OIS) is widely used. An OIS provides detailed instructions and explanations of the assembly tasks in an assembly station. Generally, an OIS provides task-level instructions and references for the human worker who is working in the assembly station. One example of an OIS is shown in Table 1. According to the OIS, the task sequence of the assembly station is pre-defined and fixed. However, in an HRC manufacturing system, the human worker's motion can be different and flexible within a task. Different workers may prefer to perform the same task in a variety of ways. With current motion capturing sensors [29], human worker's motions can be obtained. Therefore, it is possible to generalise task-level human motions as a discrete model. An example of a task-level representation is shown in Fig. 2. To apply this approach to HRC, the human worker's motions need to be further recognised and described by a mathematical model. In the next section, the motion recognition process will be introduced.

Table 1
Example of an operator instruction sheet (OIS).

Number	Activity description	Reference number
1	Take inlet resonator	27089
2	Step	16118
3	Place inlet resonator in fixture 3	27090
4	Control seats on inlet resonator	30224
5	Push to confirm	27514
6	Step	16118
7	By-pass encapsulation take 2 parts, place together	27945
8	Step	16118
9	Take throttles	28710
10	Adapt cable, take and install on throttle	29627

3.2. Motion recognition

As shown in Fig. 1, motion recognition is a pre-process of human motion prediction for HRC. The output information from motion recognition is the input of human motion prediction. Although motion recognition technologies are not the focus of this paper, the motion recognition result still needs to be analysed and cleaned for human motion prediction.

As introduced in [28], there exist different motion observation and detection technologies. Some strong and well-developed motion recognition technologies possess higher observation reliability but are limited in application feasibility, whereas other weak and evolving technologies possess lower observation reliability but can be applied in more practical situations. In this paper, both strong and weak technologies can be applied to an HRC system. For the strong motion recognition technologies, RFID tags can be used as an example. RFID tags are widely used in the current assembly line. RFID tag detection relies on the distance between the human body and the detector. In a part-taking motion, an RFID tag is fixed on the worker's clothes, and an RFID sensor is placed near the parts storage. The observation probability can be generalised as a step function:

$$P_h = \begin{cases} 1 & if \quad detected \\ 0 & otherwise \end{cases} \tag{1}$$

Table 2
Comparison of popular statistical models.

Statistical model	Advantages	Disadvantages
K-Nearest Neighbours	Simple	High computational cost for large data set.
Hidden Markov Model	Flexibility of training and verification, model transparency [30]	Many free parameters need to be adjusted [30]
Support Vector Machine	Different Kernel functions can be applied [31]	Number of support vectors grows linearly with the size of training set [32]
Artificial Neural Network	Capable of detecting complex nonlinear relationships between variables [33]	"Black box" nature introduces uncertainty [33]

For the weak motion recognition technologies, vision-based motion sensors can serve as an example. Vision-based motion sensors rely on the captured visual data. In the part-taking motion, the start of the motion can be defined when the arm starts to approach the parts storage. The end of the motion can be defined when the arm takes assembly part in hand. The closer to the end of the motion, the higher probability the motion is detected. The observation likelihood of a vision-based motion detector can be generalised as a continuous detection distribution:

$$P_l = \begin{cases} P \quad (o_{s:e}) \quad ifdetected \\ 0 \quad otherwise \end{cases} \tag{2}$$

where $o_{s:e}$ represents the observation of a gesture from the start to the end.

3.3. Statistical model selection

As shown in Fig. 1 and above sections, the input to human motion prediction is the result from human motion recognition. The output of human motion prediction is a prediction probability of a human worker's following motion which can be used in the assistive robot motion planning for HRC. The human motion prediction problem can be seen as a machine learning problem. The results of human motion recognition can easily be discretised. Therefore, several standard machine learning classification solutions can be applied. As introduced in Section 2, previous researchers have applied machine learning algorithms such as HMM, SVM, KNN, HSOM and dynamic bag-of-words to the human motion recognition and prediction problem [13–15]. A comparison of popular statistical models is given in Table 2. Among these algorithms, HMM is a well-developed discrete sequence based algorithm. Markov chain is a well fit to the applications of human motion prediction for HRC. The hidden state transition can also be used in scenarios that highly uncertain results are generated by some weak motion recognition technologies. Therefore, it is reasonable to utilise HMM for human motion prediction in manufacturing context. The HMM algorithm for human motion prediction will be introduced in the next section.

4. HMM human motion prediction

In this section, a brief introduction to HMM is presented. The assembly task representation in the HMM context is analysed. Finally, an HMM solution for human motion prediction is illustrated.

4.1. Hidden Markov model

HMM is a statistical Markov model with hidden states. The states in HMM is not observable. The hidden states have different transition probabilities. The output generated from the states is observable. Each state has a probability distribution of generating different outputs. As the example shown in Fig. 3, an HMM can be defined from the following elements [34]:

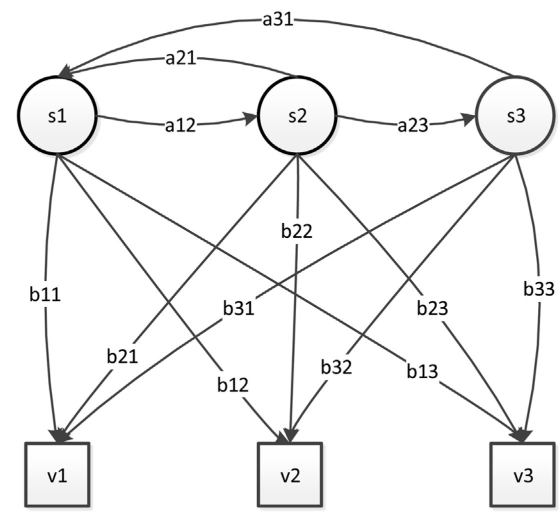


Fig. 3. Example of a hidden Markov model.

- The states are denoted as $S = \{s_1, s_2, \cdots, s_N\}$. N is the number of states in the model. The state sequence is $Q = \{q_1, q_2, \cdots, q_t\}$. The state at time t is q_t.
- The observation symbols are denoted as $V = \{v_1, v_2, \cdots, v_M\}$. M is the number of distinct observation symbols per state. The observation sequence is $O = \{o_1, o_2, \cdots, o_t\}$. o_t is the observation at t.
- The state transition probability distribution is $A = \left\{a_{ij}\right\}$, where

$$a_{ij} = P\left(q_{t+1} = s_j | q_t = s_i\right), 1 \leq i, j \leq N. \tag{3}$$

- The observation symbol probability distribution is $B = \left\{b_j(k)\right\}$, where

$$b_j(k) = P\left(o_t = v_k | q_t = s_j\right), 1 \leq j \leq N, 1 \leq k \leq M. \tag{4}$$

- The initial state distribution $\pi = \left\{\pi_i\right\}$ where

$$\pi_i = P(q_1 = s_i), 1 \leq i \leq N. \tag{5}$$

It is possible to summarise from the above that one complete HMM requires the specification of parameters N and M, observation symbols, and probability measures A, B, and π. A compact notation is introduced to indicate the complete model parameters:

$$\lambda = (A, B, \pi) \tag{6}$$

In the next section, the HMM representation of an assembly task will be introduced.

4.2. Task representation

As Fig. 4 shows, in this paper, the representation of a human worker's motions is a linear sequence. For each task, different

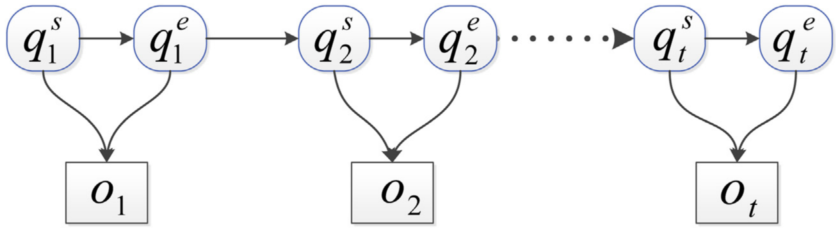


Fig. 4. An HMM model representation of a human worker's motions.

motion sequences can be observed from various human workers. In this model, the human worker's motions are modelled as a Markov process that each motion starts after the end of the previous motion. q_t^s represents the start of a motion t. q_t^e represents the end of the motion t. The motion is presented between q_t^s and q_t^e. On shop floor, the industrial robot needs to respond in a continuous time domain. However, the system models an HRC task as a discrete HMM model. Therefore, during each motion, only one observation o_t is generated. The time between two motions is ignored.

The observation of motion q_t is o_t. Therefore, the observation probability given the start and finish of the motion can be described as:

$$P\left(o_{s:e}^t | q_t^s, q_t^e\right) \tag{7}$$

Eq. (1) can be explained in an HMM model:

$$P_h(o_{s:e}^t|q_{s:e}^t) = \begin{cases} 1 & if \quad detected \\ 0 & otherwise \end{cases} \tag{8}$$

where $P_h\left(o_{s:e}^t|q_{s:e}^t\right)$ represents the strong motion recognition technologies. As explained earlier, the motion recognition technologies represented by Eq. (8) possess higher observation reliability.

The observation of HMM model requires discretised probability input. Therefore, Eq. (2) can be discretised as:

$$P_l(o_{s:e}^t|q_{s:e}^t) = \begin{cases} L_h & if \quad L_h \le P(o_{s:e}) \le 1 \\ L_l & if \quad L_l < P(o_{s:e}) < L_h \\ 0 & if \quad 0 \le P(o_{s:e}) \le L_l \end{cases} \tag{9}$$

where $P_l\left(o_{s:e}^t|q_{s:e}^t\right)$ is the probability of motion recognition results. $P\left(o_{s:e}\right)$ represents the observation probability of a motion from the start to the end. L_h and L_l are parameters that represent the limits of high and low detection probabilities. The parameters can be adjusted according to different motion detectors. As explained in earlier sections, the weak motion recognition technologies represented by Eq. (9) possess lower observation reliability.

4.3. HMM solution

As introduced by Rabiner [34], three fundamental problems can be solved by HMM in real applications:

- Given observation sequence $O = \{o_1, o_2 \cdots o_t\}$ and a model $\lambda = (A, B, \pi)$, how to compute the probability of the observation sequence $P\left(O|\lambda\right)$;
- Given observation sequence $O = \{o_1, o_2 \cdots o_t\}$ and a model $\lambda = (A, B, \pi)$, how to choose the optimal state sequence $Q = \{q_1, q_2 \cdots q_t\}$; and
- How to adjust model parameters $\lambda = (A, B, \pi)$ to maximise $P\left(O|\lambda\right)$.

In this paper, the observation sequence $O = \{o_1, o_2 \cdots o_t\}$ is known, whereas A and B need to be learned. The prediction of a human worker's motion mainly relies on A. Therefore, the third problem needs to be solved.

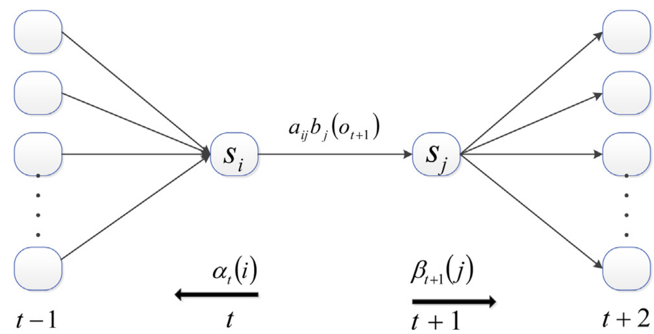


Fig. 5. The HMM model forward and backward procedure [34].

EM (expectation-modification) method [34] can address the problem described above. $\xi_t(i,j)$ is defined as the probability of being in state s_i at time t, and state s_j at time $t+1$, given the model and the observation sequence:

$$\xi_t(i,j) = P\left(q_t = s_i, q_{t+1} = s_j | O, \lambda\right) \tag{10}$$

As shown in Fig. 5, we introduce the forward and backward procedures [34]. The notation $\xi_t(i,j)$ can be re-written as:

$$\xi_t(i,j) = \frac{\alpha_t a_{ij} b_j o_{t+1} \beta_{t+1}(j)}{P(O|\lambda)} = \frac{\alpha_t a_{ij} b_j o_{t+1} \beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t a_{ij} b_j o_{t+1} \beta_{t+1}(j)} \tag{11}$$

where $\alpha_t(i)$ is the forward variable:

$$\alpha_t(i) = P\left(o_1, o_2 \cdots o_t, q_t = s_i | \lambda\right) \tag{12}$$

$\beta_t(i)$ is the backward variable:

$$\beta_t(i) = P\left(o_{t+1}, o_{t+2} \cdots o_T | q_t = s_i, \lambda\right) \tag{13}$$

$\gamma_t(i)$ is defined as the probability of being in state s_i at time t, given the observation sequence $O = \{o_1, o_2 \cdots o_t\}$ and model $\lambda = (A, B, \pi)$. It is possible to find that:

$$\gamma_t(i) = \sum_{j=1}^{N} \xi_t(i,j) \tag{14}$$

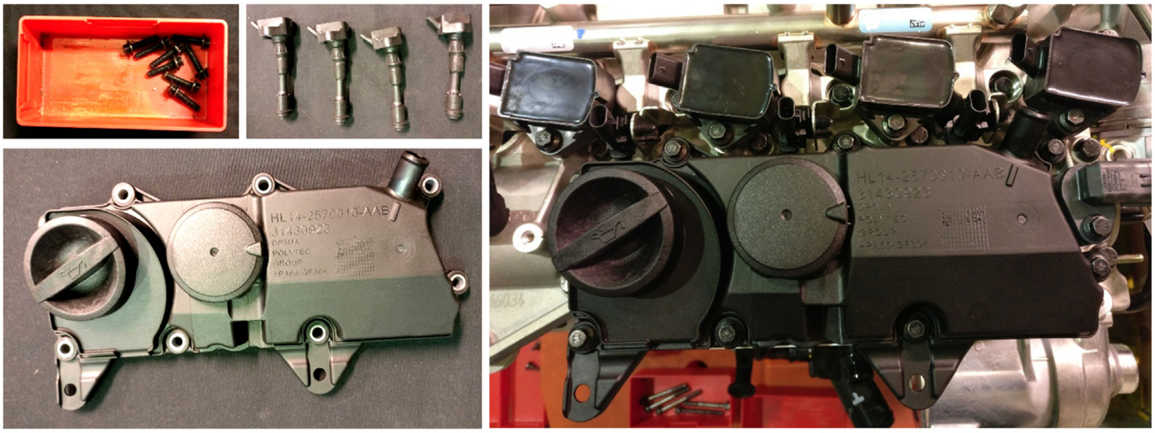
therefore:

$$\bar{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \tag{15}$$

$$\bar{b}_j = \frac{\sum_{\substack{t=1 \\ s.t. o_t = v_k}}^{T} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)} \tag{16}$$

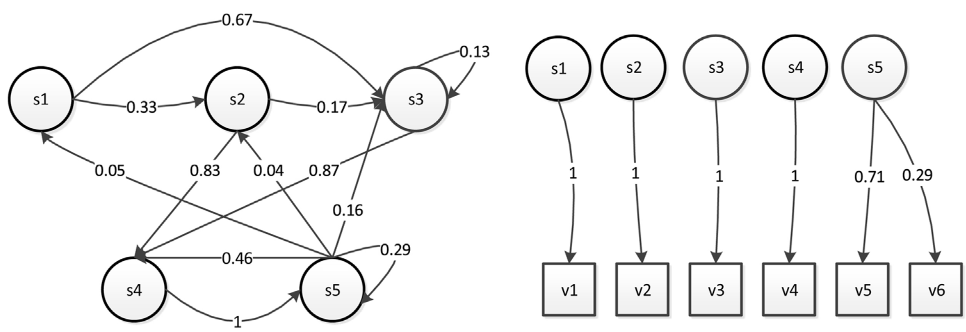
given:

$$\sum_{j=1}^{N} \bar{a}_{ij} = 1, \quad 1 \le i \le N \tag{17}$$



(a) (b)

Fig. 6. Example assembly task (a) parts before assembly; (b) the car engine after the assembly.



(a) (b)

Fig. 7. HMM state transition and observation probability graph of the assembly case (a) state transition probability matrix graph; (b) state observation probability graph.

Table 3
States and observation symbols defined for the assembly task.

States	States meaning	Observation symbols	Symbols meaning
s_1	Take screwdriver	v_1	Take screwdriver observed
s_2	Take big part	v_2	Take big part observed
s_3	Take small part	v_3	Take small part observed
s_4	Take screw	v_4	Take screw observed
s_5	Assembly	v_5	Assembly observed (with low probability)
		v_6	Assembly observed (with high probability)

$$\sum_{k=1}^{M} \bar{b}_j(k) = 1, \quad 1 \le j \le N \tag{18}$$

After A and B are computed, $\lambda = (A, B, \pi)$ is known (π can be selected). Since A indicates the state transition probability distribution, state prediction becomes possible. In the next section, a car engine assembly task will be analysed to test the presented method.

5. Experiment

5.1. Car engine assembly task

Car engine assembly is a complicated process. In this paper, a car engine assembly task is utilised to demonstrate the potential of human motion prediction as an HRC application. The parts before assembly are shown in Fig. 6(a), the right corner of which shows four electric control plugs. Each plug needs to be plugged in the engine and fastened with one screw. Fig. 6(a) also shows a plastic cover that needs to be placed on top of the engine and fastened with eight screws. Fig. 6(b) shows the car engine after the assembly task.

5.2. Case study result

To represent the case study above, five different worker motions are defined:

1. Take a screwdriver.
2. Take the plastic part (take a big part).
3. Take an electric control plug (take a small part).
4. Take a screw.
5. Assembly the screw with the screwdriver (assembly).

Four of the motions (take a screwdriver, take a plastic part, take an electric control plug, take a screw) can be detected by RFID tags. One of the motions (assembly) can be detected by vision-based motion observer. Therefore, the states and the observation symbols are defined in Table 3. The five different states are: $S = \{s_1, s_2, s_3, s_4, s_5\}$. According to previous sections and

Eqs. (8) and (9), the six different observation symbols are: $V = \{v_1, v_2, v_3, v_4, v_5, v_6\}$.

In this case study, a human worker is invited to perform the same assembly task for ten times. The initial motion is defined as s_1: take a screwdriver. The record of the assembly task is used for HMM training. The trained state transition probability distribution matrix graph is shown in Fig. 7 (a). The state observation probability graph is shown in Fig. 7 (b). The differences between weak and strong motion recognition technologies are well illustrated by the observation probability graph. Also, it can be reflected from the state transition probability graph that the worker explored many different assembly motion sequences. Compared to s_1 and s_5, s_2 s_3 s_4 have less uncertainty with regard to the next state. s_5 has many different next states. However, s_5 is the end of a 'sub-sequence'. Therefore, it is reasonable to have different possibilities after assembly. It is also noticed from the observation probability graph that sometimes v_6 is observed after v_5.

6. Discussions

The case study showcased one example of human motion prediction for HRC. Although the worker explored different assembly motion sequences, there are still patterns that can be used to predict the worker's motion for HRC. As mentioned earlier, s_2, s_3, s_4 have comparatively certain next states. Therefore, it is possible to control an industrial robot to prepare or help accordingly. s_5 has many state transition probabilities. However, the transition probabilities to s_1 and s_2 are rather small. In this HRC application, these two possibilities can be ignored. In this case study, the resource of the components is not considered yet. In the HRC manufacturing environment, the number of the components is fixed for each assembly task. The available assembly components can be used to improve motion prediction result. It is worth to mention that the unstableness of the current vision-based motion recognition technology also affects the prediction result. To solve the problem, v_6 and v_5 are defined as observations with high probability and low probability, respectively. By changing detection probability limit, it can be utilised to eliminate a 'false alarm'. It is also possible to combine different motion detection and recognition technologies to increase the system robustness. A false-correction system can be designed to further improve the robustness of the HRC system.

7. Future works and conclusions

In future works, the assembly resources can also be considered into human worker's motion prediction. Assembly resources give a major constraint on human worker's motion. The human motion prediction can be more accurate with assembly resources considered. As mentioned in the previous section, the combination of different motion recognition technologies can increase the system's robustness. Therefore, the fusion of motion recognition technologies can also be considered in the future work. Besides, the human motion prediction system needs to be tested in a real production environment with more workers and assembly tasks involved. By applying to different scenarios, the system's reliability can be further tested.

To recap, in this paper, an assembly task is modelled as a sequence of human motions. HMM is applied for motion sequence modelling. Existing human motion recognition techniques are used in motion recognition. A case study of human motion prediction is performed. The potential possibilities to apply human motion prediction in HRC at task level are demonstrated. The result of the case study is also discussed, based on which future research work is planned with anticipation.

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