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Applications of Artificial Intelligence in Safe Human- Robot Interactions

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ABSTRACT: The integration of industrial robots into the humanworkspace presents a set of unique challenges. This paper introduces a new sensory system for modeling, tracking, and predicting human motions within a robot workspace. A reactive control scheme to modify a robot's operations for accommodating the presence of the human within the robot workspace is also presented. To this end, a special class of artificial neural networks, namely, self-organizing maps (SOMs), is employed for obtaining a super quadric-based model of the human. The SOM network receives information of the human's footprints from the sensory system and infers necessary data for rendering the human model. The model is then used in order to assess the danger of the robot operations based on the measured as well as predicted human motions. This is followed by the introduction of a new reactive control scheme that results in the least interferences between the human and robot operations. The approach enables the robot to foresee an upcoming danger and take preventive actions before the danger becomes imminent. Simulation and experimental results are presented in order to validate the effectiveness of the proposed method.

KEYWORDS: Artificial neural networks, collision avoidance,human-robot interactions, motion planning, obstacle modeling, robot sensing systems, self organizing feature maps.

I. INTRODUCTION

Since their inception, robots manipulators have become an integral part of industrial automation, resulting in much higher productivity while relieving humans from laborious tasks. Today, one of the most prominent milestones luring the robotic community is the integration of a robot's and a human's workspace. While motivated by in-depth research, it is not difficult to imagine the socioeconomic benefits of an interactive environment in which robots and humans can share their workspace. At the same time, the prospect of introducing robots into the human environment has illuminated a universe of safety concerns among standardization bodies, robotic manufacturers, and the researchers as well. This is simply due to the fact that existing safety norms are all founded on one fundamental notion that is the isolation of the robots from their surroundings, which is at odds with the requirements of an interactive environment. Thus, much research has focused on developing a new breed of safe and intelligent robots that can share a common workspace with humans to perform common tasks either collaboratively or individual tasks amicably. In this regard, a significant body of the work has focused on mechanical design of such robots, among which spherical joints, compliant joints, distributed parallel actuation, and variable stiffness actuation are most no-table. Another important issue for successful integration of the human's and robot's workspaces is motion planning and control. This is where conventional offline planning techniques that require complete knowledge about the static environments are deemed ineffective in highly dimensional configuration spaces and crowded environments. The search for a feasible path in such cases becomes exceedingly complex and time-consuming.

The unstructured and time-varying nature of the new interactive environments mainly due to the unpredictable human motions exacerbates the problem even further. A model for the human motion is hardly available. Thus, the integration of sensor-based online techniques with offline motion planning seems necessary. The online sensor information is used to modify a nominal predefined path so that the robot can still reach its intended goal while avoiding obstacles.

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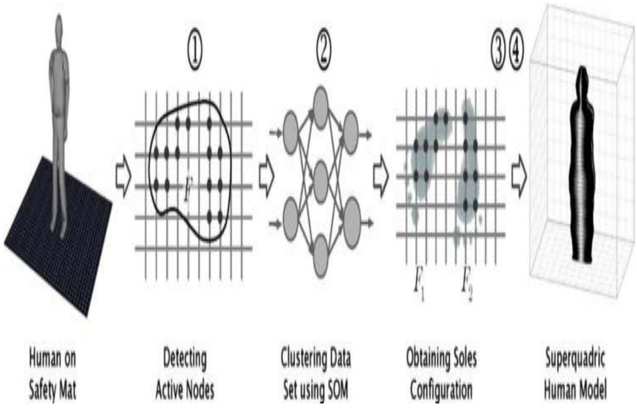


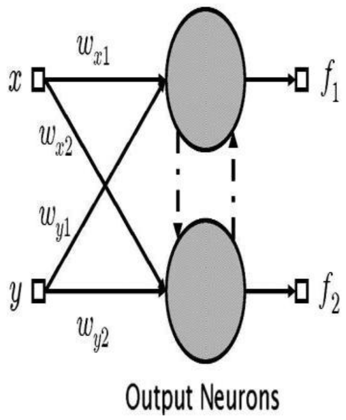
Fig 1.Process of building a human model using sensory information.

II. HUMAN MODELING

In the first part of this paper, a new sensory system for modeling and tracking human motions is introduced. The main components of the sensory system are shown in Fig. 1. The sensory system employs a safety mat, or a mat for short, and a software module for human modeling. The mat consists of a number of pressure-activated nodes. Each node on the mat has fixed coordinates with respect to a known reference frame. Under the human body weight, a set of nodes F = {(xj,yj)|j = 1, . . . , n} are activated across the mat (step 1). This set is then clustered into two subsets F1 and F2, corresponding to each foot using a SOM network (step 2). Using these subsets, the human body orientation and its location are derived (step 3). This information along with average human body dimensions is then used in order to obtain a model of the human (step 4). In what follows, each of these steps are explained in detail.

A. Safety Mat

The safety mat refers to a sensory device that can detect obstacles (e.g., humans), track their motions, and predict their near-future locations. The safety mat has a structure not unlike those used in computer keyboards. It is constructed using two rubber sheets, each of which are embedded with a number of parallel wires. The wires on one sheet are perpendicular to those on the other sheet. The sheets are separated using a spacer (a sponge with holes that coincide with the wire intersections). This arrangement provides a set of pressure-activated nodes



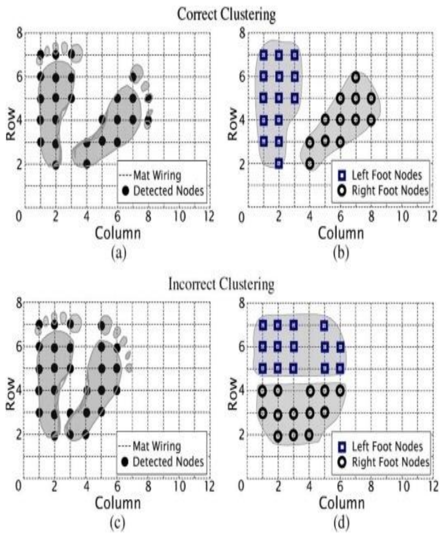


Fig. 3. Results of clustering by SOM (considered resolution is 6 cm). First case, correct clustering: (a) Detected nodes and (b) clustered nodes. Second case, incorrect clustering: (c) Detected nodes and (d) clustered nodes.

B. Data Processing Using a SOM

For a human obstacle, the output of the mat consists of a set of activated nodes F. In order to determine human body orientation and location, this set needs to be first divided (clustered) into two subsets F1 and F2, corresponding to each foot (i.e., $F1 \cap F2 = \emptyset$ and $F1 \cup F2 = F$). The two subsets can be used to obtain the orientation of each foot and, subsequently, the body orientation. To this effect, we take advantage of a special class of ANNs, known as SOM [27]. These types of networks are highly suited for discovering statistically salient features of time-varying data sets while no prior training of the network is required [28]. Thus, a SOM network seems a suitable candidate for clustering the data set representing human footprints. A SOM network with a single layer of the output neurons, as shown in Fig. 2, was used in our case. The input

$$(f_1, f_2) = \begin{cases} (1,0), & \text{if } v_1 > v_2 \\ (0,1), & \text{if } v_1 \leqslant v_2 \end{cases}$$

wherevi = wxix + wyiy (i =1 ,2) is the induced local field and wxi and wyi are the synaptic weights connecting the inputs to each output neuron, respectively. Each output corresponds to one foot, i.e., the samples that activate f1 are assigned to subset F1 and those that activate f2 to subset F2.

The competitive learning of the network can be achieved using a randomized train of samples from F. Only the synaptic weights of the winning neuron are modified. The Kohonen formula is used for this purpose [28]. For each sample (i.e., (xj,yj)€ F), the required changes for (wxi, wyi) are given by

$$(\Delta w_{xi}, \Delta w_{yi}) = \begin{cases} \eta\left((x_j, y_j) - (w_{xi}, w_{yi})\right), & \text{if } \substack{f_i=1 \\ i=1,2} \\ (0,0), & \text{otherwise} \end{cases} \quad (2)$$

whereη is the learning-rate parameter. Note that all weights are initially set to zero. In this way, each output neuron is associated to a subset selected from the original input set by modifying its synaptic weights to the center of the subset.

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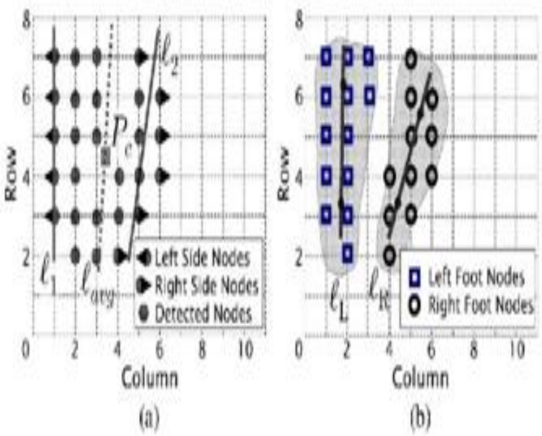

Fig. 4. (a) Side nodes and the resulting border lines for a connected sample set. (b) Clustered sample set after eliminating uncertain nodes.

C. Obtaining Body Orientation and Its Location

Having clustered the nodes into two subsets F1 and F2, the orientations of each sole and, hence, the orientation of the body can be obtained. The orientations of the soles are given by the lines _L and _R connecting the centers of the forefoot to the heel in each sole, respectively [Fig. 4(b)]. It is worth mentioning that the nodes corresponding to the forefoot and the heels are also identified using a SOM network. Considering four subsets obtained in this way (two for each sole) and assuming natural feet configuration (i.e., feet are closer at the heels making an acute angle between them), the front and the back of each sole will be determined [Fig. 4(b)]. The orientation of the human body α can now be obtained as the average of sole orientations. Moreover, the center of the body (xob, yob) is obtained as the midpoint of the line connecting the centers of the heels. These values will be used in a super quadric-based model in order to obtain a model of the human body.

D. Model of the Human Body

The human body (when standing) can be considered as an unduloid like surface (not considering the gaps between legs, arms, and flanks) with a variable cross section at various heights [25], [26]. The cross section can be formulated using a modified representation of Lame's curve used for representing super quadric functions as

$$\left(\frac{x_r}{g_1(z)}\right)^{2\varepsilon} + \left(\frac{y_r}{g_2(z)}\right)^{2\varepsilon} = 1$$

where

$$x_r = \cos\alpha(x - x_{ob}) + \sin\alpha(y - y_{ob})$$
$$y_r = -\sin\alpha(x - x_{ob}) + \cos\alpha(y - y_{ob})$$

and ε is a positive real number whose value determines the global shape of the curve. Also, (xob,yob) represents the body center in the x–y plane of a universal frame {U}, and α is the orientation of the body defined as the rotation angle between the frame assigned to the body {H} and the universal frame {U}about the z-axis. The body orientation and its center were obtained using the method discussed in the previous section. Moreover, g1 and g2 are scaling functions that determine the radius of the super quadric shape as a function of z (0 <z h), and h is the human height.

III. CONCLUSION

This paper has presented the results of a study on a sensory system and a reactive control scheme intended for HRI applications. A SOM network and super quadric functions were utilized to obtain an accurate model of the human using the information provided by the sensory system. The simplicity and accuracy of the sensory system suggested numerous benefits in comparison with other conventional sensing modalities. It was shown that, by using a feed forward ANN, human motions could be predicted and integrated in the control of the robot. A new prediction-based reactive control strategy has been pro-posed, and its advantages have been demonstrated using simulation and experimental results. The results for conventional impedance- and prediction-based reactive control strategies have been compared, and the effectiveness of the proposed control in avoiding interferences between the human and robot operations has been demonstrated.

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