An Intuitive Binary Work-Condition Map for Interactive Learning of Ergonomic Arm Postures

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***Abstract*— Safety and health of human workers are always the most important factors in the design and evaluation of a human-involved production process. While safety is usually associated with physical injuries instantly caused by collisions or impacts between human workers and machinery, ergonomics or human factors are more concerned with chronic health risks incurred by inappropriate interactions (especially repetitive and standing ones) among humans and other elements of a system, which has equal importance as the safety has and is receiving more and more attention in robotics community. Placement of ergonomic human body posture under a specified work condition is one of the essential topics in ergonomics, which is addressed in this paper. An ergonomic work condition can be measured by multiple criteria, which reflect the biomechanical properties of human body, such as muscle force based fatigue, joint torque and manipulability. To facilitate the decision making on the selection of ergonomic human arm posture, an intuitive binary work-condition map is proposed to explicitly state the arm configurations which meet all the requirements of the task-related criteria. To enhance the performance of learning ergonomic arm postures through this binary map, an interactive learning phase is introduced to assist human workers in acquiring knowledge of placing hand orientation and elbow position.**

***Index Terms*— Binary work-condition map, Ergonomic arm posture, Interactive learning**

I. Introduction

Ergonomics of human workers is an important aspect that enables safe and efficient manufacturing process. This truth is in both cases when the humans are working on their own and when they are working with machines, such as collaborative robots. In the latter case, the collision between the human and the robot is one of the key elements that impacts the safety. To reduce these risks, methods have been proposed to detect and avoid collisions [1], [2] or reduce their impact when they occur [3], [4].

On the other hand, improper working postures that produce excessive joint torques or fatigue are equally detrimental to health and safety of the human in the long run [5], [6]. To prevent such working postures, various indicators can be used to help optimise human working posture [7], [8]. When a human is collaborating with the robot, we can use the robot to optimise the collaborative task execution based on the dynamical models of the human worker. Methods in [9], [10] allow the robot to plan the optimal handover of tools between human and robot by considering various factors, such as human dexterity and joint torques. Methods in [10], [11] enable the robot to detect the overloading joint torques of the human and make the human to change it online by physical guidance. Other methods in [12], [13] let the robot to estimate the human worker's muscle fatigue and then minimise it by reconfiguration of task execution.

In [4], the authors proposed a concept called *Safety Map*, which used the information about robot inertia in different states of the workspace in combination with human injury data to give the workers an idea about the safety of interaction. In [9], the authors proposed a concept called *Interaction Workspace*, which provided a map of the workspace that indicated what positions are most suitable for task execution. Each position had an index value that depended on several quality criteria, such as human joint torque and dexterity. The index values could be represented by a colour map (one side of colour spectrum for unfavorable values and the other side for favorable values). Nevertheless, the overall index in each position was calculated by a weighted sum of criteria and the contribution of each criterion can be unclear to the worker, as well as the value itself. Specifically, it is not intuitive what a specific value means, especially if a casual worker is not an expert in the field of ergonomics.

To resolve the above-mentioned issue, we propose a novel concept called *Work-Condition Binary Map*. Unlike the method in [9], that uses weighted sum of various quality measures, our method uses a threshold based approach for various quality criteria to obtain the overall ergonomics index at different positions of the workspace. This index is therefore binary and should therefore be much more intuitive and clear. For example if the index is one (logical true) in a given position, it means that all quality measures are above the respective thresholds, which can be defined by established safety and health standards and set by experts. If it is zero (logical false), then it means that a given working position does not satisfy all the standards. Furthermore, the index across the workspace can then be clearly illustrated to the non-expert workers by a binary map.

II. Workflow Framework of the Interactive Work-Condition Binary Map

An interactive work-condition binary map is proposed in this paper to guide human workers to place their arms

*This work was supported by project "MADE Digital - driving growth and productivity in manufacturing through digitalization" funded by Innovation Fund Denmark, and it was also supported by the SDU I4.0 initiative.

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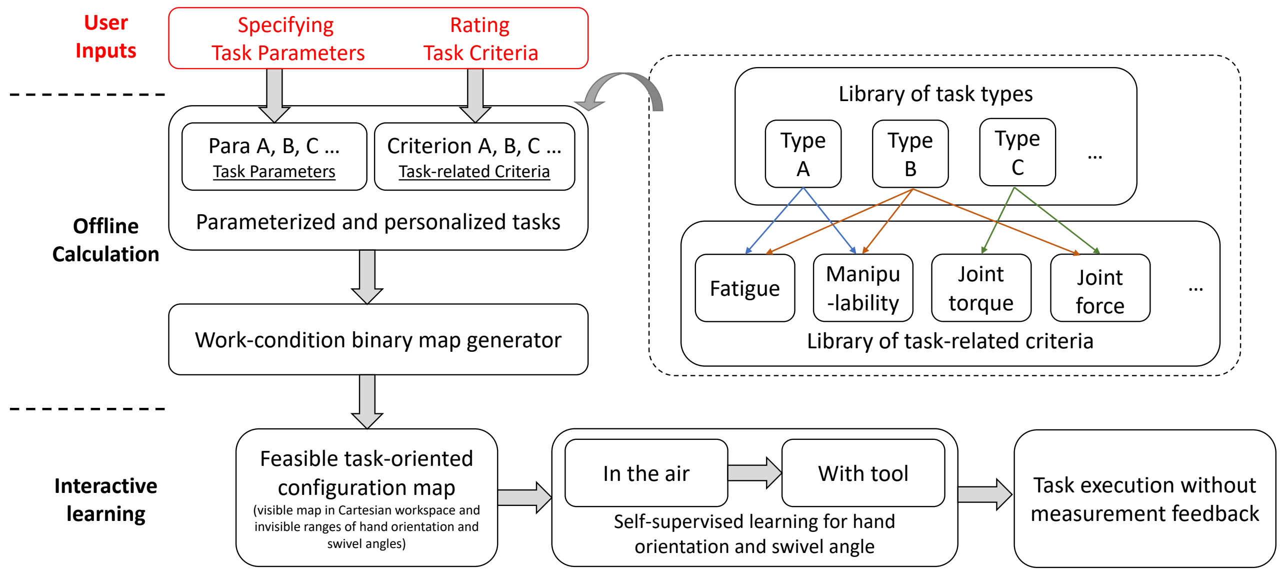

Fig. 1: An overall diagram of the generation and usage of the proposed interactive task-oriented work-condition binary map.

in appropriate postures for performing quasi-static manipulation tasks, e.g., polishing and drilling tasks, in a safe and ergonomic way. This binary map takes multiple task-related criteria into account, and is created by simulation results based on an upper limb dynamic model in OpenSim [14]. This map can be used to provide human workers with posture guidance for accomplishing tasks independent, or can be shared with collaborative robots working together with human co-workers to optimize the collaboration manner for better work condition of humans in the context of human-robot collaboration. The workflow framework of the proposed interactive work-condition binary map is shown in Fig. 1.

Once a human worker expects to perform a specific task, we assume this task belongs to a certain task type and this task type is associated with either single criterion or multiple criteria, which are used to evaluate whether a human arm posture is appropriate for this manipulation task. One task type library and one criteria library can be predefined according to an interested application domain. Different task types have different sets of associated criteria shown at the top-right corner of Fig. 1. For instance, for large force-producing tasks with short duration, the resultant torques and compression forces at human joints are highly relevant for evaluating the risk of possible joint injury; while for high-precision operations with long duration, the two criteria of muscle force related fatigue and manipulability have to be considered carefully to reduce the fatigue level and guarantee the quality of operation.

When all the relevant criteria are determined according to the associated task type, a user (human worker) will be asked to rate the degree of requirement for each criterion in a three-level way, i.e., "high", "medium" or "low". The reason we employ simpler three-level rating system instead of specifying specific numbers for criteria is that we believe the degrees or levels are more understandable and user-friendly for non-professionals (in terms of ergonomics domain). Nevertheless, these input criteria levels will be transformed to the corresponding numerical intervals for calculating and creating the binary map afterwards (invisible to users). Assume x^i_{min} and x^i_{max} are the minimum and maximum values of criteria i, a threshold value, x^i_{th}, can be defined to evaluate if criteria i is satisfied, which means a posture fails to meet the requirement of criteria i if the value of criteria i at this posture is lower than x^i_{th}. To determine how good the posture meets the requirement of criteria i, mapping relationships below can be used:

$$
\begin{aligned}
L^i_{low} &= \left[x^i_{th},\ x^i_{th} + \alpha x^i_{range}\right], \\
L^i_{medium} &= \left(x^i_{th} + \alpha x^i_{range},\ x^i_{th} + \beta x^i_{range}\right], \\
L^i_{high} &= \left(x^i_{th} + \beta x^i_{range},\ x^i_{max}\right], \\
x^i_{range} &= x^i_{max} - x^i_{th},
\end{aligned} \tag{1}
$$

where $0 < \alpha < \beta < 1$. L^i_{low}, L^i_{medium} and L^i_{high} indicate three different levels of how good criteria i is satisfied, which can be specified by the user as part of inputs. An example of the three-level division can be defined by $\alpha = 1/3$ and $\beta = 2/3$ (evenly divided). The three level intervals can be also divided unequally depending on the application. Please note that even though some existing technical specifications or standards can be used to specify x^i_{min}, x^i_{max} and x^i_{th} for some of the criteria, some other criteria, such as muscle force based fatigue/endurance criteria, have to be calibrated personally with an individual human operator to determine x^i_{min}, x^i_{max} and x^i_{th}. Transformation from criteria levels to numerical intervals can be executed after all the criteria are well calibrated. Besides the task criteria rating, task parameters also need to be specified for a specific task. For

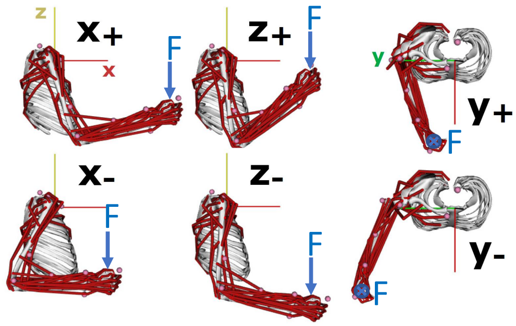

Fig. 2: Discretization of arm posture in terms of hand position in the proposed work-condition binary map.

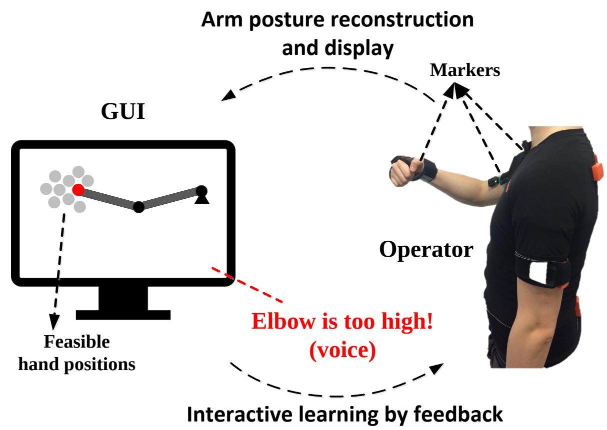

Fig. 3: Diagram of interactive learning for ergonomic hand orientations and elbow positions.

example, a drilling direction has to be determined before a drilling operation. The task parameters can also include some constrains on the arm posture in terms of position and/or orientation of hand or elbow position. Specifying task parameters and rating task criteria are the user inputs for generating such a work-condition binary map.

These user inputs are passed on to a work-condition binary map generator for calculating the feasible complete configuration map for this parameterized and personalized task, of which the corresponding task parameters will be used to specify the setting for this quasi-static force-producing task including the position, direction and magnitude of an external force applied at the human arm and imposed posture constraints; while the personalized degrees of all the relevant criteria will be employed to evaluate if an arm posture meets the task requirements and human factors.

$$\begin{aligned} I(\boldsymbol{c}) &= I_1 \wedge I_2 \wedge \ldots I_n, \\ I_i &= \begin{cases} 1 & \text{if } I_i \in L^i \\ 0 & \text{if } I_i \notin L^i \end{cases}, \end{aligned} \tag{2}$$

where I is the overall binary index for a given human arm configuration $\boldsymbol{c}$, calculated by binary AND operation among the individual binary indices of various quality criteria, i.e. $I_i,\ i = (1, 2, \ldots n)$. The individual binary index is evaluated by checking if the corresponding criteria value is within the personalized requirement level L^i.

To evaluate all the possible arm postures subject to joint limits, the whole configuration space of human arm is discretized in terms of the *Cartesian-Posture-Swivel-Angle* (CPSA) representation of human arm configuration [15]. In this CPSA representation, a human arm configuration is expressed by a 3-Degree-of-Freedom (DoF) position and 3-DoF orientation of human hand, plus 1-DoF swivel angle of the elbow, which is determined by the angle between a shoulder-elbow-wrist human arm plane and a vertical plane [16]. In Fig. 2, the discretization of arm posture in terms of hand position is exemplified. A hand position step size will be predefined in advance. Every possible arm posture will be tested under the same external force (e.g., F shown in Fig. 2) in an individual OpenSim simulation automatically, and be analyzed by (2) according to the calculated values of all the associated criteria. If all the criteria are satisfied and $I(\boldsymbol{c}) = 1$, the arm posture sample will be labelled as a feasible configuration otherwise it will be discarded as an infeasible posture. In the end, only the feasible hand positions will be presented visible as a set of Cartesian points to the users; while the corresponding feasible hand orientation and swivel angle will be explored by the user himself/herself in an interactive way. The whole process aforementioned will be conducted offline and automatically through batch-processing OpenSim simulations. It is worth noting that the discretization of task criteria rating and human arm configuration actually reflect the nature of the proposed "Binary" map, and it is believed that this "black-and-white" strategy will simplify the decision making on the posture selection with consideration of multiple criteria for workers who are not experts in ergonomics, compared to other methods where arm configurations are labelled with continuous values and they often need to be interpreted with professional knowledge about the criteria.

After the offline calculation stage, we obtain a complete and feasible configuration map (binary map). However, only the feasible hand positions will be displayed through a GUI (Graphical User Interface) for the moment, while the feasible hand orientations and swivel angles will have to be learned in the following interactive learning stage. The rationale of this strategy is that the relative hand positions (with respect to human torso) are usually easier to be understood and therefore memorized by humans, compared to the relative hand orientation and elbow swivel angle. In the interactive learning stage, the human operator will be first asked to attach a set of markers on the anatomical landmarks of his/her arm, and the current arm posture will be captured by a Motion Capture system (Mocap) and reconstructed in the GUI in real time [17]. When the current hand orientation and elbow swivel angle meet the personalized criteria requirements according to the simulation results, the current hand position point in the GUI will flash in green, otherwise it will flash in red with a voice prompt indicating an infeasible arm posture is caused by either inappropriate hand orientation or elbow position. If the hand is not placed in any of the feasible hand positions (the distance between the current hand position and the nearest feasible hand position is larger than the step size), no position point will flash indicating the hand is outside of the feasible Cartesian workspace. This interactive learning process is illustrated in Fig. 3 with an example of non-ergonomic elbow position. Through this interactive self-supervised learning manner, the operator is able to establish an intuitive sense of how he/she should place the arm in appropriate configurations for performing the specified task. This self-supervised learning can be further divided into practicing in the air and practicing with the real tool to help the user memorize the desirable arm configuration step by step. After a considerable amount of interactive learning and practice, which can be evaluated by a criteria of the correct rate of a large number of arm placements, the operator can get ready to execute the actual task without the assistance of the measurement feedback.

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