

6th CIRP Conference on Assembly Technologies and Systems (CATS)

The Working Posture Controller: Automated adaptation of the work piece pose to enable a natural working posture

The Duy Nguyen^{a,*}, Christian Bloch^a, Jörg Krüger^{a,b}^aTechnische Universität Berlin, Pascalstr. 8-9, 10587 Berlin, Germany^bFraunhofer Institut für Produktionsanlagen und Konstruktionstechnik (IPK), Pascalstr. 8-9, 10587 Berlin, Germany* Corresponding author. Tel.: +49-30-314-28737; fax: +49-30-314-29526. E-mail address: theduy.nguyen@iat.tu-berlin.de

Abstract

We present a novel approach to prevent awkward working posture by automatically assessing and optimising the work place for a given task. Our system is called the Working Posture Controller (WPC) and enables to accomplish tasks in a natural posture by adapting the pose of work piece to be processed. Unlike other approaches to prevent posture-related Musculo-skeletal Disorders (MSDs), our system is able to propose an immediate adjustment in the process neither requiring tedious manual planning nor expert knowledge. Additionally, the proposed solution is personalised to the anthropometry of the user. First experiments on a simulated height-adjustable platform reveal promising results.

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Peer-review under responsibility of the organizing committee of the 6th CIRP Conference on Assembly Technologies and Systems (CATS)

Keywords: 3D-Image processing; Human Centred Automation; Assembly; Ergonomics

1. Introduction

According to Parent-Thyrion et al.[1], the 2 biggest groups of occupational diseases among assembly workers in the EU are muscular pain (22.8%) and lower back pain (24.7%). These figures indicate that Musculo-skeletal disorders (MSDs) pose a serious threat for companies and their workforce reducing productivity and worker health. Additionally, MSDs result in a high financial loss for the employer: In the EU, the costs are estimated at 0.6% - 1% of the gross national product, which translates into hundreds of billion Euros[4].

Due to the impact of this problem, various groups, e.g. [2,3], conducted research on the causes of MSD. Putz-Anderson et al.[3] have identified force (over-)exertion, monotonous strain over a long term period, awkward static working posture and combinations thereof as the most common risk factors. Solutions to prevent the MSD risks factors have been proposed from different scientific disciplines including Human factors or Engineering. The effectiveness of the approaches can be evaluated according to the "Hierarchy of Hazard Control"[5,6]. Solutions which eliminate the risk or substitute it with something harmless are the most preferred ones. If there is no such solution, engineering controls, which isolate and guard the worker from the still existing hazard, are recommended. If this is not possible, administrative controls teach the worker how to appropriately deal with the hazard or schedule the tasks in a way

such that the time exposed remains short. If all these measurements are infeasible, the last resort remains to equip the workers with personal protective equipment to lower the effects. In case of MSDs, we simplify this scheme into 2 classes: the higher ranked measurements which enable the worker to completely avoid the hazard (elimination, substitution and engineering controls) and the lower ranked ones which aim to reduce the exposure time or intensity (engineering or administrative controls, personal protective equipment). The transition between these groups is continuous. In brief, factory planners shall always attempt to implement the highest ranked control if possible. Unfortunately, there is often a trade-off between effectiveness of a solution and the effort to implement it. For many processes, MSD hazards can be eliminated by careful work place design through ergonomics experts. However this task is tedious as it involves an extensive analysis of the process and individualised solutions. Solutions using intelligent sensors and actuators are especially interesting, since they offer the potential to overcome this trade-off. Effective strategies can be implemented while the tedious parts thereof can be automatised to reduce costs. An example are digital human tools, which can nowadays take over evaluations of solutions by simulating the real process[7,9]. However, at the moment, some human expertise is still required to produce an appropriate solution. While force exertion and monotonous strain can be effectively prevented without human involvement e.g. by Human Robot Collaboration[11] or Cobots[8], overcoming awkward posture still requires human intervention, since a solution has to be tailored to various aspects, e.g. anthropometry or task. This

work attempts to tackle this problem by proposing an assistance system, which automatically evaluates the worker's posture according to ergonomic guidelines and adjusts the work place in case of unsuitable working posture. The novelty is that the adjustment happens without human involvement right in the process. There is no need for a specialist to manually assess and re-design the work place. Additionally, the system is able to react to an unfavourable posture within a few seconds. To sum up, our main contributions are:

- We propose a novel type of assistance system, which corrects the worker's posture by adjusting the processed work piece pose.
- We provide the algorithms to implement such a system using a height-adjustable platform.
- We show in first simulations that that most hazards can be tackled by the system.

The rest of the paper is structured as follows: Section 2 provides a brief overview of how MSD risks are tackled at the moment using automation and information technology. Furthermore, we describe the works from human factors and digital human modelling, which relate to ours. Section 3 describes the methods used to implement the Working Posture Controller (WPC). In section 4, we present the setup and results of our first experiments. Finally, in section 5, we sum up the insights learned from this work and point out future tasks.

2. Related work

There has been vivid research in the field of MSD prevention using intelligent equipment. Solutions using automation and information technology mostly work on the higher levels of the Hierarchy of Hazard control.

On the elimination and substitution level, there are three approaches: Cobots[8], Exo-Skeletons[12] and workplace design with digital human models[7,10]. Cobots and Exo-skeletons both attempt to avoid overexertion of force by delegating the execution of force intensive tasks to actuators. Thereby, it is essential that the system can interpret the human intention. The communication interface between human and robot is realised by force-torque sensors. In brief, motion and actions of the worker are amplified in power.

Digital human models aim to simplify the tedious task of workplace design. Instead of physically building each solution candidate and manually assessing it, the insights are obtained through simulation of process and human behaviour. Additionally, the system can automatically assess the digital worker's posture. While the evaluation is dramatically simplified, the process to select the appropriate solution still requires human knowledge about the best practices in work place design. Furthermore, the solution cannot easily be adapted to different anthropometrics.

To sum up, the biggest drawback of approaches so far is that they still require some human expertise to be created. Moreover, the implementation of the measure requires a remarkable time effort. Cobots and Exo-Skeletons are interesting approaches, since they enable to eliminate the risk with dramatically reduced time and human expertise. Unfortunately, they cannot ensure that awkward posture is avoided. Our system

attempts to fill this gap by automatising the workplace design process enabling an immediate reaction of the work place when necessary. To achieve this, 2 tedious and knowledge-intensive sub-tasks need to be automatised: ergonomic assessment of the posture and ergonomic optimisation of the workplace.

At the moment, there are 3 possible approaches to conduct ergonomic posture assessment: (self-) reports, observational methods and direct measurements[13]. Reports and interviews of the workforce after the process are hard to automatise and do not allow immediate feedback. Direct measurements often require time-consuming calibration of the tools. Hence, observational methods, such as EAWS[15] or RULA[14] appear to be the most promising approach for our system. In brief, they provide a set of pre-defined ergonomic criteria which are evaluated through mere observation. The user has to classify each occurring posture in the process. A risk evaluation can then be derived from the occurring posture classes. The methods mostly differ in the level of detail they provide, and thus, in the user group they are designed for. While some ergonomics assessment methods only output binary statements, whether the risk is acceptable, others provide numeric risk scores, which are especially suitable for workplace design.

The second task involves finding a adjustment of the workplace to enable the task accomplishment in a natural posture. To decide whether a specific adjustment can achieve this, the working posture after it has to be simulated and predicted (posture prediction). This task has been researched in the field of digital human simulations. Having a method to predict the posture given the adjustment, there is a need for a second method to come up with an appropriate adjustment in a given solution space (posture optimisation). In literature, two main approaches have been proposed for posture prediction - using Machine Learning e.g. Neural Networks[18,19] and using optimisation techniques[17]. The former models the human behaviour through a set of existing examples. The latter uses an objective function whose optimum represents the predicted posture. For posture optimisation, there are at the moment only approaches using brute-force search[16] or manually created solutions considering best-practices[7].

3. The Working Posture Controller (WPC)

The Working Posture Controller intends to close the scientific gap described before by enabling automated, adaptive and immediate workplace design. The work flow is depicted in Fig. 1. The WPC consists of 2 parts: a sensor and an actuator. The sensory system is placed at the work place and observes the worker while performing the tasks. It monitors and assesses the postures of the worker during the process. When the risk exceeds an acceptable threshold, the system notices the worker and proposes a re-adjustment of the work place to enable a more natural working posture. Awkward posture is adopted when the work piece is in bad range for the task. Hence the spatial relation between worker and work piece has to be altered, such that the range requirements can be met with still adopting a natural posture. The modification of the spatial relation is achieved by attaching the work piece to an actuator, which can modify its pose. If the user accepts the proposed adjustment, the sensor initiates the actuator to move the work piece. An other way to understand the system and its sub-tasks is to interpret the WPC



Fig. 1. Example application scenario of the WPC. The first 2 images show a non-optimal pose of the work piece forcing the human to adopt awkward posture when working on it. The last image shows a configuration leading to a natural work posture.

as a closed-loop controller which attempts to adjust the posture as close to the ergonomically ideal one as possible (see Fig. 2).

For effective implementation of this concept, we have identified following technical requirements: Firstly, it is essential that the feedback is provided within a few seconds to actually reduce the risk. Moreover, the method needs to be as least invasive as possible. Each piece of equipment worn by the user can potentially limit the freedom of movement. Finally, depending on the options of an enterprise, different types of actuators (industrial robot, height-adjustable platform, tilting table) can be employed. The WPC shall be able to consider the available degrees of freedom (DoF) of the actuator and determine the best solution within these limitations.

In the following, the methods used for the WPC are described more in detail. The workflow is structured into the steps "Posture Assessment" and "Posture Optimisation".

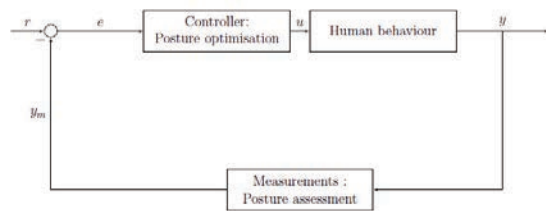


Fig. 2. The WPC interpreted as close-loop controller.

3.1. Posture Assessment

This section briefly describes how our system observes the occurring working postures during a process and computes a numerical score representing the ergonomic risk. The Posture Assessment component has been subject of our previous work[20].

As sensory hardware, we use the Microsoft Kinect®. The sensor provides colour images as well as depth maps. The latter image type contains the distance of each pixel to the nearest obstacle in the scene. Hence, depth maps provide 3D information, which significantly simplifies the task of human motion analysis. The biggest advantages of the Kinect as sensor are its cost efficiency (price around 200 \$) and that the Posture Assessment does not require the user to wear additional expensive equipment. We consider cost efficiency as a key to provide enterprises world wide access to our solution.

In order to obtain the risk score, we employ the Ergonomics Worksheet (EAWS) [15]. It is one of the most popular methods

Table 1. EAWS (v. 1.3.3) for standing posture classes

Posture No.	Image	Name
2		Upright standing
3		Bent forward (20 – 60°)
4		Strongly bent forward(> 60°)
5		Arms at / above shoulder
6		Arms above head level

Table 2. Values of the EAWS (v. 1.3.3) for standing posture classes

Posture No.	Fraction of time in %									
	5	7.5	10	15	20	27	33	50	67	83
2	0.7	1	1.5	2	3	4	5	8	11	13
3	2	3	5	7	9.5	12	18	23	32	40
4	3.3	5	8.5	12	17	21	30	38	51	63
5	3.3	5	8.5	12	17	21	30	38	51	63
6	5.3	8	14	19	26	33	47	60	80	100

used for observation-based posture assessment. The EAWS assigns a pre-defined score for each occurring static posture in the process depending on its estimated physical load and share of time. Originally, it requires a human expert to monitor the process. Automatising the EAWS requires the system to recognise the pre-defined postures in each image frame. After an analysis of the characteristic postures to be distinguished by the EAWS (see Tab. 1), we choose to place the camera from the side position, since it reveals the most distinctive features for the posture assessment. Our algorithm is tailored to the side perspective. However, this limitation can be solved by using multiple sensors and generating the required perspective from the perceived point cloud. This extension will not be considered in this paper. To recognise the posture from an image frame, we compute body landmarks. In the following, they will be referred by "joints" (see Fig. 4 left). The main idea of the localisation procedure follows the "Analysis-by-synthesis" approach. The task is to find the parameters of a human model, which creates an artificial image (model image) most similar to the observed camera image. The components to be instantiated in this approach are: image features, model, model image and similarity function between image features and model image. We design these components as follows:

Image features: We compute the silhouette of the segmented worker as image features. The segmentation mask can be obtained by background subtraction in the depth image.

Model: We use a 2D kinematic chain with rectangular segments to model the human body (for terminology, see Fig. 4

left). The parameters of the model are represented by a vector of joint angles q and a vector of segment lengths l . In this work, we only consider 2D postures of the EAWS and leave out the detection of lateral bending and rotation of the trunk. This means that in the most severe case, our system misses 30 EAWS points from the not detected 3D postures. The reduced dimensionality and number of parameters helps us to apply an efficient parameter optimisation scheme.

Model image: The model image is obtained by masking out all the pixels filled by the model.

Similarity measure: The similarity measure between image features and model image is obtained by computing the overlap between each model segment and the silhouette image. To obtain one numeric similarity measure, the mean of the overlap values is computed. We can efficiently search the optimal parameters for the model by A* search[21]. In brief, given the input images, the work flow is as follows:

1. Compute the segmentation of the worker (see fig. 3 middle) using background subtraction.
2. Determine the Center point of the foot region P_{Foot} (see Fig. 4 left). This can be done by computing the centroid of the lowest rows of the segmentation mask.
3. Optimise the human model, such that the similarity function between image features and model image is maximised (see fig. 3 right).
4. From the optimised model, extract the joint angles q (see Fig. 4 left).
5. Assign a posture label to the joint angle vectors using a pre-trained classifier.



Fig. 3. Tracking work flow: Color image (left), segmentation mask of the subject (center), optimised human model (right).

3.2. Posture Optimisation

The goal of this component is to adjust the work piece pose to enable a natural working posture. We assume that the work piece is attached to an actuator. The algorithm takes angles q and segment lengths l of the output model (see Fig. 4 left) from section 3.1 and outputs the actuator configuration and the resulting posture q^* (see Fig. 4 right). The values q_i represent the angle between a segment (straight line) and its predecessor in the kinematic chain (dashed line). q_1 represents the angle between segment and global y-Axis. Note that q_i can be positive as well as negative depending on which side of the local y-Axis the current segment is tilted. We consider a height-adjustable platform or table with 1 DoF, the height, as actuator. This is the

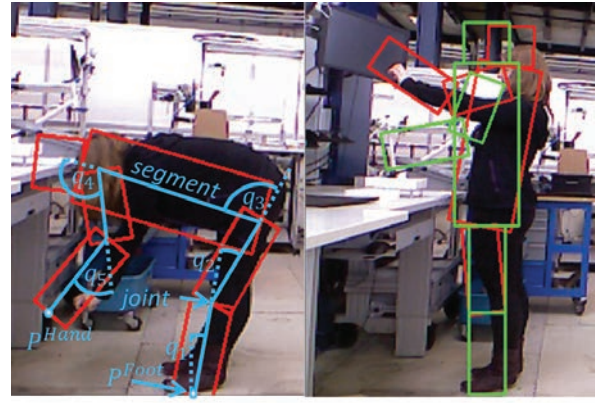


Fig. 4. Left: Terminology of the model used. Right: Current posture (red) and optimal posture (green)

most simple case. Extending the framework for more complex kinematics e.g. robotic manipulators, requires integrating kinematic constraints and inverse kinematic computations, which is out of the scope of this paper.

Given an input posture, the goal is to determine the height where the worker is able to adopt a natural posture (goal 1) and accomplish the task (goal 2). If it is not possible to achieve both goals, a height value shall be determined which represents the best compromise. As described in section 2, first, an algorithm to predict the worker's posture is needed. We choose an optimisation-based approach, since the posture prediction task can then be naturally modified to fulfil the posture optimisation task obtaining the optimal actuator configuration.

Nomenclature

q	Joint angle vector $q = (q_1, \dots, q_6)$
w	Weight value between 0 - 1
V_Θ	Working direction angle expressing the angle between global y-Axis and last segment
P	2D point with its components P_X and P_Y
Y	Height value

The optimisation approach models the choice of the subject's posture by an objective function $f(q)$. This function takes the posture q as argument and assigns high values for unlikely postures and low values for likely postures. We define this function as follows:

$$f(q) = \underbrace{w(q - q^{Best})^2}_{goal1} + (1 - w) \underbrace{(V_\Theta - V_\Theta^{Before})^2}_{goal2} \quad (1)$$

with

$$V_\Theta = \sum_i q_i$$

$f(q)$ combines goal 1 and goal 2 in a weighted sum. The first objective states that the worker will choose a posture which is near to an ergonomically ideal posture q^{Best} . According to the EAWS, q^{Best} is a standing posture with arms below shoulder level (see Tab. 1 Posture No. 2). The second term states, that the worker attempts to adopt a posture where the working direction angle V_Θ remains as close as possible to the one chosen

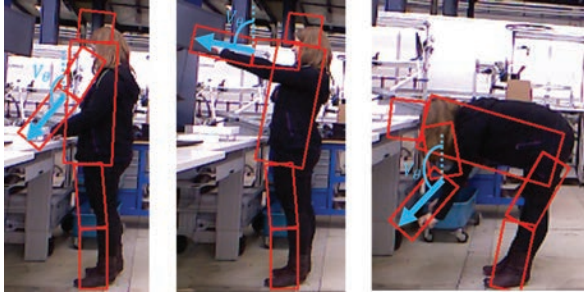


Fig. 5. Visualisation of the working direction angle V_θ

before (V_θ^{Before}). The working direction angle V_θ denotes the direction the forearm of the worker is pointing at (see Fig. 5). The term ensures that after the optimisation, the worker is still able to accomplish the task as the spatial relation between forearm and work piece is preserved. Furthermore, we express the position of the hand P^{Hand} (see Fig. 4 left) as a function of the posture q . The position can be computed using forward kinematics:

$$P^{Hand} = P^{Foot} + \sum_i R(\sum_{j=0}^i q_j) * l_i \quad (2)$$

with

$$R(q) = \begin{pmatrix} \cos q & -\sin q \\ \sin q & \cos q \end{pmatrix}$$

In order to predict the posture, given a working height Y , we optimise the objective function f with added constraints:

$$q^* = \min_q w(q - q_{Best})^2 + (1 - w)(V_\theta - V_\theta^{Before})^2 \quad (3)$$

s.t.

$$\begin{aligned} q_{Min} &\leq q \leq q_{Max} \\ Y - \epsilon &\leq P_Y^{Hand}(q) \leq Y + \epsilon \end{aligned}$$

The first constraint models the space of feasible postures. By limiting the angular space, infeasible postures can be excluded from the solution space. The second constraint enforces the y-value of the hand $P_Y^{Hand}(q)$ to remain within certain range. When predicting the posture for a given working height, we set ϵ to a value representing a small area around Y , e.g. 10cm.

When finding the optimal posture given minimum height Y_{Min} and maximum height Y_{Max} achievable by the actuator, the second constraint is modified to:

$$Y_{Min} \leq P_Y^{Hand}(q) \leq Y_{Max} \quad (4)$$

Since objective function and constraints in the optimisation problem eq. (3) are non-linear, we choose the Sequential Quadratic Programming (SQP) algorithm to determine q^* .

4. Experimental results

In our experiments, we intended to answer 2 questions: How similar are the EAWS scores computed by our system to the ones obtained by manual assessment? How effectively can the risk be reduced? Our test dataset contains image sequences of 9 subjects performing various standing EAWS postures (see Tab. 1). The set of subjects comprises 1 female and 8 males with anthropometric heights roughly ranging between 1.5m and

2m. We placed the sensor at a distance of about 3m. The subjects performed working motions adopting the postures in a randomised order (see Fig. 5 for example frames). The heights of the hands ranged from 0cm (strongly bent) to 293cm (hands above head). The duration of each posture was arbitrarily chosen to be between 1 and 3 seconds. Afterwards, the postures occurring in the dataset have been classified by a person different from the one creating the posture sequence. With this design, we enforce that the human only labels the sequences based on the image data and not on other prior knowledge.

4.1. EAWS scores

Using the manually determined posture labels we first computed their time share. Afterwards, we determined the partial EAWS scores by looking up the score for each posture according to their time share (see tab. 2). The final score is the sum of all partial scores. To obtain the automatically determined scores, we performed a 9 fold cross-validation. For each sequence, we classified the joint angle vectors with a Support Vector Machine trained with the other 8 sequences. This makes it possible to evaluate how well the system works on new, unseen data. Fig. 6 shows the results. The maximum difference of scores is about 10. Moreover, there are 3 datasets where manually and automatically determined scores are equal.

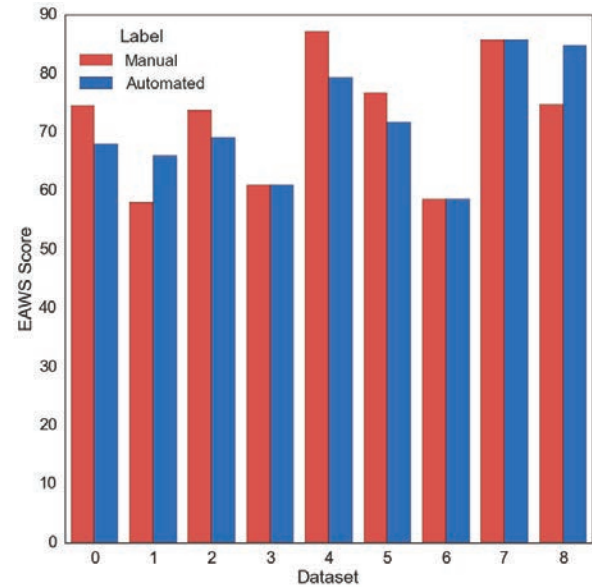


Fig. 6. Comparison of manually and automatically determined EAWS score for each dataset. A dataset comprises a sequence of postures.

4.2. Posture optimisation

In our simulated optimisations, the range of hand heights has been narrowed to 61cm – 171cm. We then computed the EAWS of the optimised postures for each dataset. The optimised postures have not been manually classified, but automatically by our system. This could introduce certain error rate, however, since our classification rate is over 90%, we believe that the

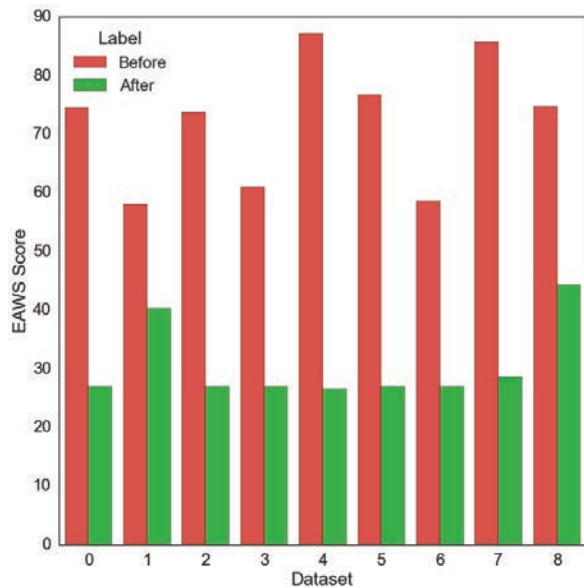


Fig. 7. EAWS score Before and After automated adjustment.

error can be negated. The results can be seen in Fig. 7. The EAWS defines scores above 50 as critical and above 25 as considerable. Only scores below 25 points are completely acceptable. As can be seen in the results, the system manages transform all critical postures into at least partly acceptable ones. The majority of the posture sequences are fully acceptable.

5. Conclusions

We have presented a novel approach to tackle awkward posture at work. Our system is able to bridge the trade-off between effectiveness and effort. Moreover, we have introduced a framework to automatically design the work place using non-linear optimisation techniques. This has its advantages to traditional brute-force approaches, since detailed solutions can be generated without human involvement.

As future work, we plan to extend the Posture Optimisation framework to operate with more DoF as it is in the case of industrial robots. Furthermore, we intend to consider the question of when to initiate an adaptation in order to minimise physical load as well as interruption to the work flow. Finally, there is a need to conduct studies to evaluate how practically realisable the proposed postures are since the subjects in the experiments have not performed the tasks after adjustment.

Acknowledgements

This research is funded by the German Research Foundation (DFG) in the Collaborative Research Centre (CRC) SFB 1026 Sustainable Manufacturing Shaping Global Value Creation at Technische Universität Berlin. Especially, we would like to thank Martin Rudorfer and Sebastian Schenker for the valuable feedback.

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