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Aiding Observational Ergonomic Evaluation Methods Using MOCAP Systems Supported by AI-Based Posture Recognition

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Abstract. Observational ergonomic evaluation methods have inherent subjectivity. Observers' assessment results might differ even with the same dataset. While motion capture (MOCAP) systems have improved the speed and the accuracy of motion-data gathering, the algorithms used to compute assessments seem to rely on predefined conditions to perform them. Moreover, the authoring of these conditions is not always clear. Making use of artificial intelligence (AI), along with MOCAP systems, computerized ergonomic assessments can become more alike to human observation and improve over time, given proper training datasets. AI can assist ergonomic experts with posture detection, useful when using methods that require posture definition, such as Ovako Working Posture Assessment System (OWAS). This study aims to prove the usefulness of an AI model when performing ergonomic assessments and to prove the benefits of having a specialized database for current and future AI training. Several algorithms are trained, using Xsens MVN MOCAP datasets, and their performance within a use case is compared. AI algorithms can provide accurate posture predictions. The developed approach aspires to provide with guidelines to perform AI-assisted ergonomic assessment based on observation of multiple workers.

Keywords. Artificial Intelligence, Machine Learning, Motion Capture, Wearable Inertial Sensors, Ergonomic Assessment, Ergonomic Evaluation

1. Introduction

The novel Industry 4.0 (also called the 4th industrial revolution), based on digitalization and future-oriented technologies in the field of "smart" objects, is changing the way companies understand and approach their processes [1]. Industry 4.0 comprises a large variety of concepts, where the most relevant for this paper are cyber-physical systems (CPS), adaptation to human needs, and corporate social responsibility [1].

CPS can be defined as "integration of computation and physical processes, where embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa" [2]. Physical measures are digitalized using sensors to reach this integration. However, this digitalization focusses more on produced goods, services, and the components to create

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them, rather than focusing on the role of human beings in the design of smart factories. Monitoring technologies allow the integration of human-related data into the design process, along with machines and their connectivity and interoperability features [3], making it more socially sustainable, intelligent, and flexible [4].

Monitoring technologies which focus on movement-related data are called motion capture (MOCAP). They have applications in several fields such as filmmaking, videogames, robotics, healthcare, ergonomics, and mechanics. There are three main technologies currently used within MOCAP: wearable inertial sensors, smart textiles, and image/video recognition. Wearable inertial sensors include gyroscopes and accelerometers to record motion. Inertial/magnetic measurements units are often added to compensate for possible drawback of the other sensors [5]. On the other hand, smart textiles provide standard fabrics with some kind of extra functionality, mostly within monitoring health-related variables [6]. Lastly, the current advances in artificial intelligence (AI), especially in the field of image recognition, have helped include this technology into the MOCAP field [7]. While some authors' research is done within pose estimation, where 2D images or videos are the primary sources of information [8–11], others have their focus on applying MOCAP directly to different processes/fields [12]. 2D image recognition can accurately predict specific anthropometric measurements [13], but it does not seem powerful enough to perform when the subject is moving or within the whole range of postures. On the other hand, 3D cameras (or depth cameras) can reach the highest accuracy among MOCAP systems, but they have disadvantages such as the need to have a clear sight on the target.

One application of MOCAP systems is aiding within physical ergonomic evaluations, seeking the prevention of work-related musculoskeletal disorders (WMSDs) [12]. Risk factors for WMSD include rapid work pace, repetitive motion patterns, forceful extensions, non-neutral body postures, heavy lifting, and vibration [14]. WMSDs have a high health and economical cost [15], due to factors such as work absence [16], healthcare expenditure [17], or loss of quality and productivity [18,19] among others, as well as the personal cost such as the physiological and stress problems suffered by the workers [20].

Posture-related ergonomic evaluations (referred just as ergonomic evaluations in this paper) can help to decrease the effect of these problems either by letting workers know when their postures are not good enough [21] or by designing workstations that lead the workers to have a better one [22], among others. Ergonomic evaluation methods can serve these purposes since they are applied to identify and assess risk factors in the workplace. These evaluation methods can be divided into several categories: self-report, simple observational techniques, advanced observational techniques, and direct measurement [23]. Direct measurement methods are the most objective since the results are based on analytic data, in contrast with observational methods, which rely on the subjective ergonomist´s judgment to assess the work task [24]. Observational methods are performed by looking at the work task (or on a videotape for example) and taking a few staple measures, such as the weight of the objects that the workers manipulate. Ergonomists can make use of either an existing evaluation method (Rapid Upper Limb Assessment (RULA) [25], Rapid Entire Body Assessment (REBA) [26], and Ovako Working Posture Assessment System (OWAS) [27], among others), or a custom one.

Traditionally, the attempts to automatize observational methods with MOCAP data have been based upon the premise that it is better to strictly apply the guidelines of certain method rather than apply these methods with the implicit human subjectivity. However, the judgment of an expert is not necessarily the wrong criteria for evaluation. Instead, given the power of human reasoning, they can consider several variables omitted in the ergonomic assessment method used.

Experts might have different opinions about the same posture or task when applying an ergonomic evaluation method, e.g. about whether someone is bending instead of standing straight when the posture is unclear. If a particular set of variables are analysed to differentiate between postures, and these variables are measured using MOCAP equipment, the subjectivity of the evaluation can be taken away. While MOCAP systems can accurately measure anthropometric variables, posture classification (or labelling) is done by a human. AI can both directly learn from human classification, and it can adjust its predictions to the fine refinement that the human might apply to the assessment.

This study aims to investigate the advantages of approaching observational methods with combined use of AI and MOCAP systems. In the next section, an AI-based approach to observational ergonomic evaluation methods is presented. Section 3 presents, an example of the proposed approach, applying AI-based working posture detection within OWAS evaluation method, is described, followed by a discussion of the results and a summarize of the outcome in Section 4.

2. Proposed AI-based approach to observational ergonomic evaluation methods

Humans are valuable limited resources, and many might find observation to be a tedious, time-consuming process. Moreover, observation is based on the observers' perception [24]. When it comes to perception, AI algorithms (sometimes referred to as AI models) can provide with predictions, which are probabilistic outputs of the model trained using datasets built based perception. These models are capable of achieving even lower error rate results than humans in some fields, e.g., visual recognition algorithms, which have surpassed humans in several visual tests [28]. Preventing misuse of human resources would enable performing tasks in which humans are much better than machines, such as understanding complex problems and identifying underlying patterns.

To perform the search for previous work, the following string was defined:

$$(wearable\ OR\ inertial\ OR\ mocap\ OR\ motion\ capture)\ AND\ (ergonomics\ OR\ ergonomic\ assessment\ AND\ (learning\ OR\ machine\ learning\ OR\ artificial\ intelligence)$$

From the 34 results in the Scopus database, 21 abstracts were screened, and only 7 of them were relevant for this paper [29–37]. None of the reviewed papers was using or aiding existing ergonomic assessments through learning from multiple experts' knowledge or perception. Selection schema is presented in Figure 1.

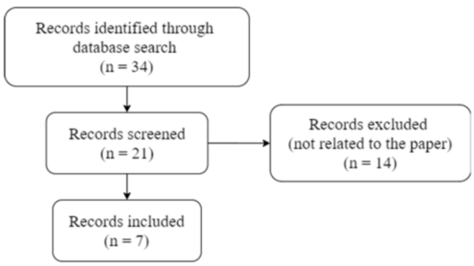

Figure 1. Flow chart of literature search and selection schema.

For the sake of generalization, fifteen different observational ergonomic evaluation methods were considered. The inputs required to perform each method can be classified into two groups [23]:

- **Objective inputs** are feasible to apply direct measurement and computing, since they rely on accurate data, such as mean power frequency (MPF).
- **Subjective inputs** are inherent to perception [38], and therefore problematic when deciding how to measure and compute them: working posture, recovery, and complex factors (environmental conditions, psychological, and individual factors, among others).

2.1. Workflow and components

In the following section, the suggested workflow is presented: from defining the problem to applying an operational AI-based solution to observational ergonomic evaluation methods using MOCAP systems. The starting point should always be particular ergonomic needs. Different problems, and ergonomic assessments available to handle them, shape the solution.

Depending on what kind of postures need to be measured, a specific MOCAP system will be more or less suitable than others. While the market is moving towards a new generation of low-cost MOCAP systems [39], certain MOCAP technologies might involve a trade-off between budget, desired accuracy, reliability, and extension of the ergonomic assessment to cover.

Existing solutions could also be a determinant factor, where used MOCAP would be a suitable, directly applicable solution. When selecting a MOCAP system, one of the criteria should be whether it is aimed to cover the entire ergonomic assessment (all the input variables are measured using MOCAP) or part of it (only certain variables).

Once data is collected, it might be possible to use an existing compatible solution (one which has the same MOCAP data). If there is no solution available, a custom one will be required, where MOCAP data will also be used to train an AI model. It will be necessary to carefully study the variables, and not include in training those not used to define a specific posture. For instance, a variable such as a neck angle most likely should not be included when aiming to predict lower limbs posture.

The AI model to use could differ from case to case. Evaluation is needed for the trained model, where MOCAP system feeds the AI model to check its feasibility. If the model is not good enough (most likely according to subjective criteria), the AI model would need to be retrained. This approach can be illustrated, as shown in Figure 2.

3. Evaluation of the suggested approach

Regardless of theoretical advantages, empirical results are desired when trying to demonstrate the feasibility of AI models. With this objective, the following use case is presented: building an AI model for posture prediction using the OWAS ergonomic evaluation method. OWAS inputs (postures) are defined descriptively in the assessment, instead of numerically, as it is done in other ergonomic assessments, such as RULA or REBA, where specific angle values are provided. Therefore, OWAS postures are subjective by nature, and different evaluations have been performed with different

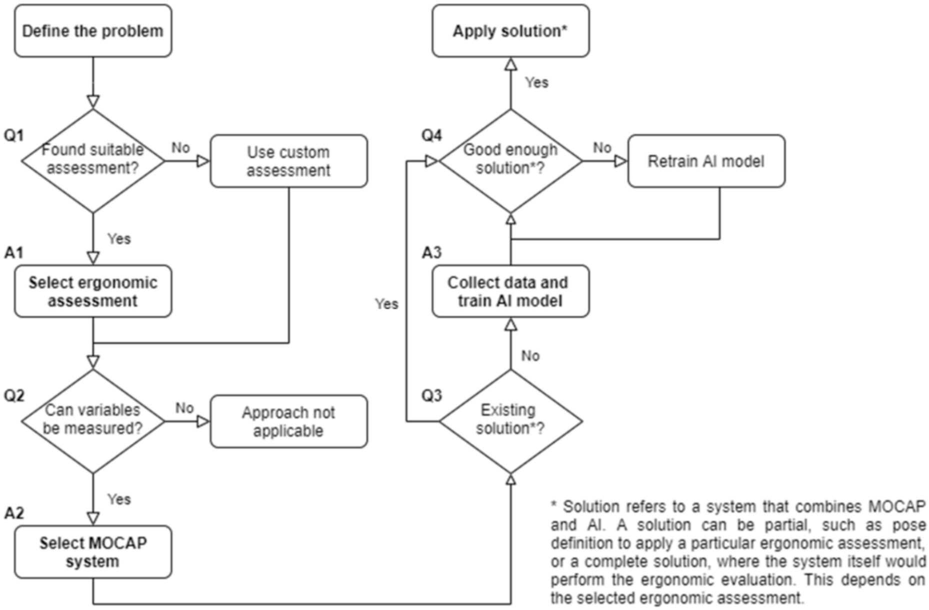

Figure 2. Suggested workflow for the presented AI-based approach.

criteria. Within OWAS, there are four different categories for back postures, three for upper limbs postures, and seven for lower limbs postures. AI can help by learning from the humans' classification, based on perception, and providing with predictions based on that training.

Other ergonomic evaluation methods would be also suitable for the case. The method itself would be a starting point for training, and the main task for AI would be to modify the original parameters of the method according to the humans' final refinement.

The task performed by the subject under study is hypothetical, where the subject moves within the range of postures which would fit in the different OWAS categories. This use case is focused on the OWAS postures detection, rather than applying the assessment strictly.

Following the presented approach, questions are answered as follows:

Q1: Found a suitable assessment?

A1: Rather than looking at suitability, OWAS is selected given its subjective nature [40], so an AI-based solution is built to potentially aid observers to have a more consistent judgement of posture classification when using OWAS.

Q2: Can variables be measured?

A2: As mentioned, OWAS does not provide with information about how to classify postures through anthropometric measurements. However, posture-related variables can be measured, since MOCAP systems provide enough information to accurately relate these variables to the labels in OWAS. The set of variables, picked to relate perception into OWAS labels, are back (in terms of inclination and rotation), upper limbs (shoulders angle), and legs (lower limbs angles). Several solutions are available to measure these variables. It is decided to use Xsens MVN [41], due to its current availability at the University of Skövde.

Q3: Existing solution?
A3: No, there are no AI models already trained for OWAS ergonomic assessment. A custom solution is required (See section 3.1).

Q4: Good enough solution?
A4: Solution is evaluated in Section 3.3.

3.1. Building an AI-based solution for the use case

A database is needed to build a custom solution, where MOCAP systems input is related to the different inputs required to perform the selected ergonomic assessment. In this case, Xsens' input is related to one of the OWAS categories [27], required to determine the posture: back posture, upper limbs posture, and legs. The database is generated using the answers from an online distributed questionnaire created by the authors of this paper. On it, participants were asked to classify 60 postures by selecting between two options, each shown in a figure including a real picture and the associated virtual representation (manikin), in one of the OWAS categories (Figure 3). At the beginning of the questionnaire, participants were asked to read the original OWAS study. The questionnaire was answered by 7 participants, being their area of expertise ergonomics (within either industry or research) and healthcare.

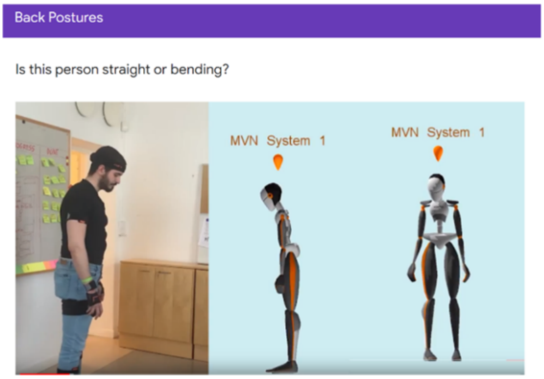

Figure 3. Example a question within the questionnaire.

Results are tabulated for AI training in Matlab. During the training stage, using Statistics and Machine Learning Toolbox and Deep Learning Toolbox in Matlab, the AI algorithms will map inputs (MOCAP data) to outputs (OWAS posture category). Ten different supervised learning algorithms (both input and corresponding output are provided during the training stage) are trained: Fine decision tree, medium decision tree, coarse decision tree, fine k-nearest neighbours (KNN), medium KNN, coarse KNN, cubic KNN, weighted KNN, and convolutional neural network (CNN). CNNs, are less sensitive to the training datasets, and therefore less affected by outliers. However, when using CNNs, it is challenging, if not impossible, to interpret the model and analyse useful information, such as the correlation between variables.

From 60 questions and 7 answers per question, the total size of the built dataset is 420. To prevent overfitting, decision trees and KNN models were trained with 70% of the dataset, with cross-validation set to 5 folds. The CNN was trained with 70% of the dataset, leaving 15% for validation and 15% for verification, using the Levenberg-Marquardt training algorithm.

The inputs used for training were joint angles values coming from Xsens. Domain knowledge is applied to reduce the number of variables, reducing the risk of misclassification, and only variables related to the posture aimed to classify are used for prediction, as is shown in Table 1. For instance, limbs information is deleted from the dataset used to predict back postures.

Table 1. Example of dimensionality reduction for AI training, divided by category. The variables (joint values) presented are named as they are defined by the Xsens system.

OWAS category	Variables used for training (joint values)
Back	Pelvis, Lower back (L5 + L3), Chest (T8 + T12)
Upper limbs	Shoulder (left and right), Upper arm (left and right)
Legs	Pelvis Lower back (L5 + L3), Upper leg (left and right) Lower leg (left and right)

3.2. Questionnaire results

Results from the questionnaire show how experts might differ when classifying certain poses. For instance, in the question shown in Figure 3, 57% of the participants classified the posture as “bent”, in contrast to 43% who classified it as “straight”. Significant differences can be found when comparing straight and bending postures. Legs and upper body rotation appear to be less problematic among the participants, with a lower degree of disagreement.

Questionnaire sections are related to the type of posture to classify: questionnaire section 1 compares straight and bent back postures back, questionnaire section 2 compares bent and a combination of bent and twisted back postures back, questionnaire section 3 classifies upper limbs posture, and questionnaire section 4 classifies lower limbs postures. Questionnaire section 5 compares two postures not included in OWAS, in which a comparison between bent and straight back, having bent legs, is made. This last section is included to compare the different experts’ judgment when classifying a posture not included in the ergonomic assessment. Figure 4 shows the disagreement ratio, comparing dominant options (the ones selected by most of the participants) with the other ones. Figure 5 illustrates an example of a uniform answer and an example of a non-uniform answer.

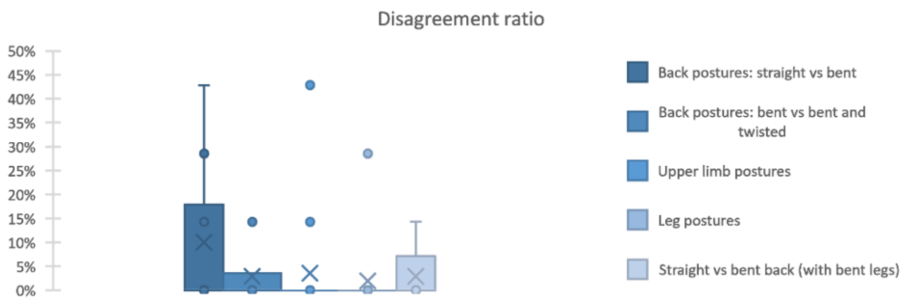

Figure 4. Disagreement ratio from the online questionnaire, comparing dominant options (the ones selected by most of the participants) with the other ones.

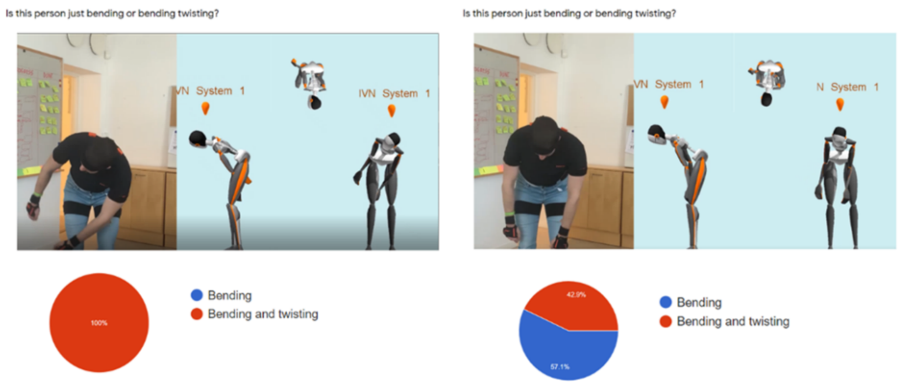

Figure 5. Example a uniformly answered question vs non-uniformly answered question.

3.3. Implementation results

Training results for each trained model are provided in Table 2. Training time for each model was shorter than a few seconds, except for the CNN, where training time was 25 seconds. When using larger datasets, training time is expected to stay relatively short in all the models, except for CNN.

Table 2. Training results for each trained model and its accuracy with the different OWAS categories. Most of the models result in high performance, indicating potential suitability of their use.

Model	Back OWAS accuracy (%)	Upper limbs OWAS accuracy (%)	Legs OWAS accuracy (%)	Avg. (%)
Fine tree	91.8	98.1	97.1	**95.7**
Medium tree	91.8	98.1	97.1	**95.7**
Coarse tree	85.7	98.1	97.1	**95.6**
Fine KNN	85.4	95.2	97.1	92.6
Medium KNN	90.7	98.1	97.1	**95.3**
Coarse KNN	79.3	55.2	97.1	77.2
Cosine KNN	92.1	98.1	97.1	**95.8**
Cubic KNN	90.7	98.1	97.1	**95.3**
Weighted KNN	92.9	98.1	97.1	**96.0**
Convolutional Neural Network	99.9	99.9	99.9	99.9

Resultant accuracy values in the OWAS back category suggest that these kinds of models are suitable for posture classification when the dataset is large enough. Upper limbs and legs predictions accuracy for the different models are the same, which would be a rare situation when using more data. More significant results would be expected if the upper limbs and legs datasets used was as large, and as varied, as the back dataset. The results obtained with CNN suggests that it is overfitting the dataset, most likely making the solution not suitable for other datasets.

4. Discussion and future work

Simple tasks, such as posture estimation within ergonomic evaluations, should not consume human time, and it could be done in an automatic, large-scale manner. Using a systematic AI-based approach to ergonomic evaluation methods, where AI is considered from the beginning, has potential future applications, including but not limited to: the study of workers behaviour to optimize workstation design and prototyping, the study of patterns which might affect the long-term worker health, or workstation reconfiguration and optimization based on worker's movements. Furthermore, the existence of MOCAP would enable the implementation of human-related data into CPS and other platforms.

Results suggest that applying AI algorithms to observational ergonomic evaluation methods could be suitable for aiding in the computation of ergonomic assessments. AI-based solutions can be built by training models based on the experts' judgment applied to data extracted from body movement. While the results are promising, some models, like CNN, seem to be overfitting, providing exceedingly high accuracy for the current dataset. Overfitting makes difficult to predict how these models would behave when using new datasets. Further testing is required to validate the different models. AI-based ergonomic evaluations are most likely to improve over time, with ergonomic experts' feedback and with the use of new datasets for training. Moreover, further study about how AI-related parameters affect predictions when using MOCAP systems is needed.

AI can work with a dataset of a particular moment in time, e.g., recognizing working postures, but also with cumulative data, using models like recurrent neural networks (RNN). These kinds of AI-models would enable the recognition of an entire range of motion-related variables, such as current working tasks or precedent postures [7]. One of the topics for future research is using task recognition for suggesting the most suitable ergonomic assessment for each case.

One of the main challenges of the presented approach is to generalize it to multiple MOCAP systems, given their differences when it comes to digitalization of motion-related data. Each system might provide data in different formats, lacking some parts of the body, or use postprocessing for various reasons, such as global position calibration. In future studies, and if a comprehensive database is aimed to be created, further discussion about a common ground for multiple MOCAP systems would be required.

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