Ergonomic Risk Assessment of a Manikin's Wrist Movements - a Test Study in Manual Assembly

A. KEYVANI*†, D.HÖGBERG‡, L.HANSON§, D.LÄMKULL√, N.DELFS‼, I.M.RHEN‡, and R.ÖRTENGREN†

† Product and Production Development Dep., Chalmers University of Technology, Gothenburg, Sweden

‡ Virtual Systems Research Centre, University of Skövde, Box 408, SE-541 28 Skövde, Sweden

§ Industrial Development, Scania CV, Scania AB (publ), SE-151 87 Södertälje, Sweden

√ Virtual Methods & IT, Volvo Car Corporation, Dept. 81620/PVÖS32, SE-405 31 Gothenburg, Sweden

‼ Fraunhofer Chalmers Research Centre, Gothenburg, Sweden

Abstract

Use of digital human modeling (DHM) tools enables early assessment of ergonomic risks in the production development process. This early risk assessment can indicate needs for preventive actions in order to decrease risks for work-related musculoskeletal disorders. A method for the assessment of physical workload has been developed, for the analysis of wrist joint data produced by a DHM tool. The method is tested in a simulation model of an actual manual assembly station in industry where it is assumed that physical workload problems exist. The results show that the method can be successfully applied on an industrial case. In addition, presumptive risks and possible diagnoses are predicted based on the similarity of the simulated task's motions with motions from other known work class profiles stored in a database based on epidemiological research.

Keywords: Ergonomic Assessment, Digital Manikins, Time-sensitive, Workload, Wrist Joint.

1. Introduction

Work-related musculoskeletal disorders (WMSD) represent a major health problem in modern industrialized nations with consequences such as considerable costs for the society and quality of life-reductions for the human (National.Research.Council 2001; Punnett and Wegman 2004). To deal with the problem, different methods for the ergonomic evaluation of the work and workplaces are developed which aim to identify and prevent risk factors for WMSD (David 2005).

Increased use of computers in design and engineering work has led to the development of different simulation and modeling software packages. Among them, digital human modeling (DHM) tools are used for simulation and visualization of human work and enable proactive ergonomics efforts early in the production development process (Woldstad 2000; Chaffin 2005; Zhang and Chaffin 2005; Chang and Wang 2007). For risk evaluation of physical load, widely used ergonomic evaluation methods, such as RULA (McAtamney and Nigel Corlett 1993) and OWAS (Louhevaara et al. 1992), are generally included in the DHM tools. However, since these methods are developed for observation-based assessments, the suitability of them for ergonomics assessment in DHM tools is questioned (Fritzsche 2010; Rhen et al. 2011). Direct measurement methods are based on the use of technical devices to measure human movements and physical exertion during work. This is to gather data in an objective manner and with high precision. Typically the data is recorded over time. In comparison, observation-based methods are based on observation of human work, leading to less precision and including some degree of subjectivity. As a consequence, observation-based evaluation methods are rougher in assessment criteria and typically also focus on static postures. However, a DHM tool can effortlessly generate large amounts of kinematic and time-varied data related to the manikin's dynamic motions.

To overcome this mismatch, risk assessment methods utilized in direct measurement research may serve as inspiration for a more suitable and sensitive approach to evaluate ergonomics in DHM tools (Chaffin 2005; Wagner et al. 2007). Moreover, considering that epidemiologic research has shown a correlation between time-related aspects, such as repetitiveness and/or joint velocities, and the development of WMSD (Bernard 1997; Nordander et al. 2013), it should be of significance to include these aspects in the risk assessment.

A method for the assessment of physical workload has been developed for the evaluation of detailed manikin output data from a DHM tool. The method being developed focuses on assessment of wrist movements since the wrist is a problematic area

*Corresponding author. Email: ali.keyvani@chalmers.se

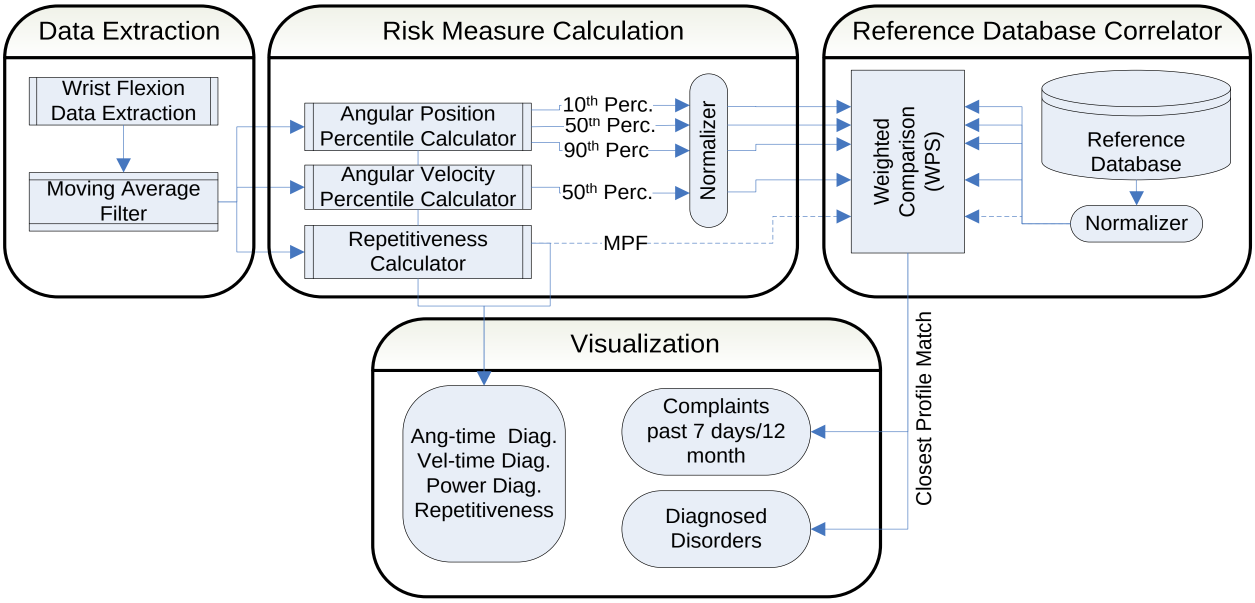


Figure 1. Risk assessment workflow and its major modules. Dash lines represent future developments.

often associated with WMSD (Nordander et al. 2013). Furthermore, the conceptual assessment method correlates the results to an epidemiologic reference database in order to predict presumptive risk factors and their assigned diagnoses. The approach is tested in a simulation model of an actual manual assembly station in industry where it is assumed that physical workload problems exist.

2. Method

The assessment method presented in this study is using the digital human modeling tool IMMA (Hanson et al. 2010) to generate dynamic (time-varied) joint data for the simulated motions. The objective is to assess ergonomic risk factors associated with the wrist movement. For doing so, kinematic risk measures are calculated using generated motion data and the output result is then compared with an epidemiologic reference database. This comparison is then visualized and presumptive implications are presented to the end-user. In other words, the assessment process includes following major steps: 1) generation of joint data in the DHM tool, 2) calculation of kinematic risk measures, 3) correlation of risk measures to epidemiologic data, and 4) visualization of data and prediction of presumptive risk factors (Figure 1).

2.1. Data Extraction

The IMMA tool generates postures by assigning a set of joint angles to the manikin's internal model (skeleton model) and the tool is able to simulate motions, e.g. representing a full work task. As a result, a motion can be represented by motion graphs which are time series of changes in joint angles. For joints with more than one degree of freedom (DOF), a motion graph per DOF is produced. In this study, wrist flexion angles are extracted from the DHM tool for risk measures calculations. The angle unit is degrees and positive values represent palmar flexion. To smooth extracted data, a filter with a moving average of 5 is applied.

2.2. Risk Measure Calculation

Three risk measures: *angular position*, *angular velocity* and *repetitiveness* (Rhen et al. 2012) are calculated for determining the presumptive risk values. Two of them, angular position and angular velocity, are used to correlate risk measures to an epidemiologic database. Angular flexion/extension values, which are extracted from wrist movements, are used to calculate 10, 50 and 90 flexion/extension percentiles. Angular velocity is also calculated and the 50 percentile value is extracted.

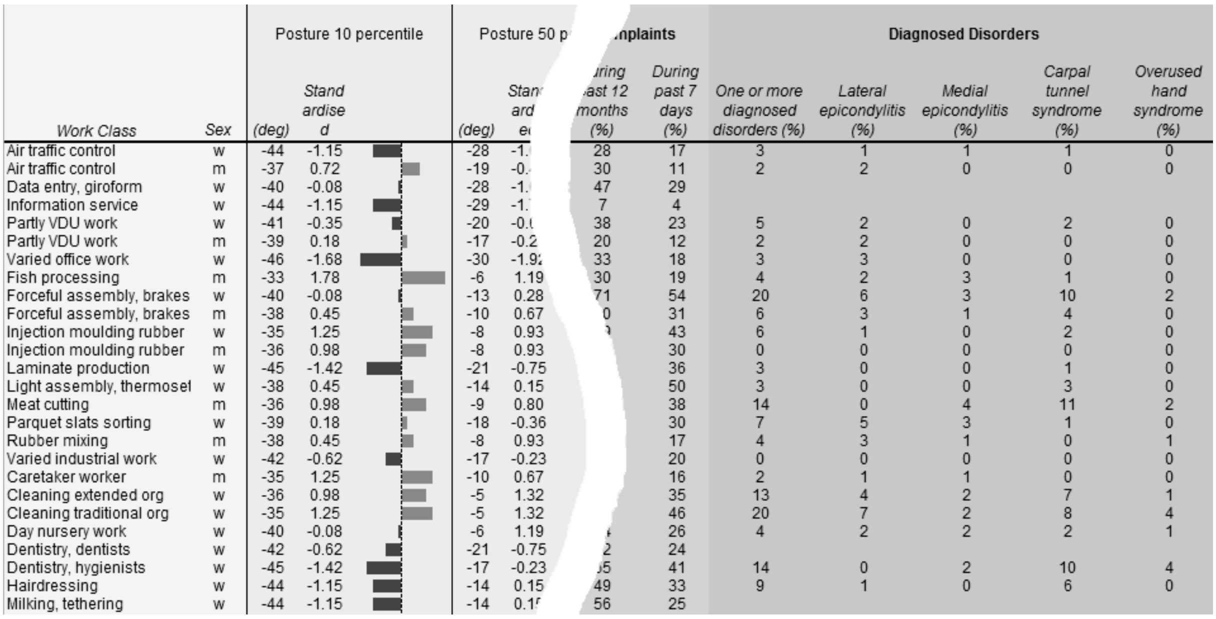
Repetitiveness in a motion can be formulated with many different methods (Rhen et al. 2011). Among them, mean power frequency (MPF) is a measure to quantify muscle activity especially when using EMG (electromyography) signals (Öberg et al. 1994) and the measure can also be used to quantify repetitiveness of movements (Mann et al. 1989; Hansson et al. 1996; Arvidsson et al. 2003). In this study, fast Fourier transform (FFT) is used to calculate the power spectrum and to derive MPF value (eq.1):

$$MPF = \int_0^F f \cdot X_f^2 df \Big/ \int_0^F X_f^2 df \qquad (1)$$

Where F is the maximum frequency analyzed in the power spectrum, X_f is the amplitude of the harmonic at frequency f, and X_f^2 is the power at frequency f.

2.3. Epidemiologic Reference Data Correlation

Once these measures are calculated, an epidemiologic reference database (ERD) based on



Work Class	Sex	Posture 10 percentile (deg)	Posture 10 percentile Standardised	Posture 50 p… (deg)	Standard…	…mplaints: …uring …ast 12 months (%)	During past 7 days (%)	Diagnosed Disorders: One or more diagnosed disorders (%)	Lateral epicondylitis (%)	Medial epicondylitis (%)	Carpal tunnel syndrome (%)	Overused hand syndrome (%)
Air traffic control	w	-44	-1.15	-28	-1.	28	17	3	1	1	1	0
Air traffic control	m	-37	0.72	-19	-0.	30	11	2	2	0	0	0
Data entry, giroform	w	-40	-0.08	-28	-1.	47	29					
Information service	w	-44	-1.15	-29	-1.	7	4					
Partly VDU work	w	-41	-0.35	-20	-0.	38	23	5	2	0	2	0
Partly VDU work	m	-39	0.18	-17	-0.2	20	12	2	2	0	0	0
Varied office work	w	-46	-1.68	-30	-1.9	33	18	3	3	0	0	0
Fish processing	m	-33	1.78	-6	1.19	30	19	4	2	3	1	0
Forceful assembly, brakes	w	-40	-0.08	-13	0.28	71	54	20	6	3	10	2
Forceful assembly, brakes	m	-38	0.45	-10	0.67	0	31	6	3	1	4	0
Injection moulding rubber	w	-35	1.25	-8	0.93	[illegible]	43	6	1	0	2	0
Injection moulding rubber	m	-36	0.98	-8	0.93		30	0	0	0	0	0
Laminate production	w	-45	-1.42	-21	-0.75		36	3	0	0	1	0
Light assembly, thermoset	w	-38	0.45	-14	0.15		50	3	0	0	3	0
Meat cutting	m	-36	0.98	-9	0.80		38	14	0	4	11	2
Parquet slats sorting	w	-39	0.18	-18	-0.36		30	7	5	3	1	0
Rubber mixing	m	-38	0.45	-8	0.93		17	4	3	1	0	1
Varied industrial work	w	-42	-0.62	-17	-0.23		20	0	0	0	0	0
Caretaker worker	m	-35	1.25	-10	0.67		16	2	1	1	0	0
Cleaning extended org	w	-36	0.98	-5	1.32		35	13	4	2	7	1
Cleaning traditional org	w	-35	1.25	-5	1.32		46	20	7	2	8	4
Day nursery work	w	-40	-0.08	-6	1.19	[illegible]	26	4	2	2	2	1
Dentistry, dentists	w	-42	-0.62	-21	-0.75	2	24					
Dentistry, hygienists	w	-45	-1.42	-17	-0.23	5	41	14	0	2	10	4
Hairdressing	w	-44	-1.15	-14	0.15	49	33	9	1	0	6	0
Milking, tethering	w	-44	-1.15	-14	0.1	56	25					

Figure 2. Snapshot from the reference database (based on Nordander et al. 2013).

the data obtained by Nordander et al. (2013) is used to compare the accounted values with previously investigated work classes in different industries. The database consists of reference values for 26 different occupation-gender profiles gathered from different studies. For each profile, the average 10^{th}, 50^{th} and 90^{th} percentiles of wrists’ angular position (flexion/extension) and average angular velocity (50^{th} percentile) are documented in the database. In addition, for each profile, the numbers of reported complaints (in percent) in past 7 days/12 months are stored in the ERD. Also, percentage of diagnosed disorders and type of diagnose, when available, are documented. A snapshot from part of the database is given in Figure 2.

In order to make a valid comparison, the calculated angular position and velocity values from the simulated task are first normalized using the mean and standard deviation from the reference database. For each profile *i*, a weighted profile score (WPS) is then calculated (eq.2). The closest match (minimum score difference) between the simulated task’s work profile and a certain work class’ work profile in the database is selected as the most appropriate work class for representing the simulated work task. Hence, complaints and diagnosed disorders associated to the selected work class are used to predict assumed risks for complaints and disorders for the simulated task.

$$WPS_i = a_1(\Delta P10_i + \Delta P50_i + \Delta P90_i) + a_2(\Delta V50_i) \quad (2)$$

$\Delta P10_i, \Delta P50_i, \Delta P90_i$ are differences in angular position percentiles (10, 50, and 90) of the simulated task and the work class profile i in the reference database. $\Delta V50_i$ is the difference in angular velocity (50 percentile) of the simulated task and the work class profile *i*. a_1, a_2 are custom weighting coefficients ($a_1 = 1, a_2 = 3$ in this study).

At the time of this study, MPF values were not available for the reference database and therefore not accounted for in the WPS calculations. However, the same approach can be utilized to consider the effect of repetitiveness whenever sufficient data is available. As a result, MPF values are only used for visualization purposes at this time.

2.4. Data Visualization

The calculated measures are visualized to the end-user in the form of both numeric values and diagrams. The available diagrams are angular position and angular velocity vs. time and frequency power spectrum. Position/velocity diagrams also show corresponding 10, 50 and 90 percentile values, and mean power frequency is illustrated in a power spectrum diagram.

Moreover, based on the resulted WPS, the presumptive ergonomic risk data from the closest profile match are visualized from the ERD. The visualized data includes complaint reports of the last 7 days/12 month and possible diagnosed disorders related to the wrist joint.

3. Results

A case from an automotive manual assembly line is selected to test and illustrate the developed risk assessment method, using the IMMA tool for simulating the work task and generating wrist motions data. The work task consists of the assembly of a CEM (central electronic module) box in a car. The assembly of the CEM is carried out on the assembly line when there is no front door or seat assembled. The car is also lifted to a height, possible to adjust by the operator to make it easier to assemble. However, the nominal position of the

CEM is in a concealed location and the operator has limited eye sight and access to the final location of assembly. The assembly task continues by removing dummy plugs and connecting cables to the CEM connectors. Finally the job is finished when the worker is going back to a standing rest neutral position (Figure 3).

A collision free path, similar to what happens in reality for assembling the CEM box, is first generated using the IPS (Industrial Path Solutions) software (Carlson et al. 2005), and then the IMMA tool is utilized to simulate the assembly worker's motions when installing the CEM box in place using the designated path. Timings of the operations are adjusted using the Operation Instruction Sheet from the original task.

Figure 3. Snapshots from three states of installing the CEM box into its place.

Having the assembly task simulated, the wrist joint flexion-extension movements of the right hand is analyzed using the dynamic wrist exposure module in the IMMA tool and the risk predictor user interface, here designed in Excel. The angular position data for the right wrist, which is selected for analysis, is first resampled and interpolated in 20Hz using spline method and then filtered using a moving average filter to remove noises existing in the signal. The data is then exported to Excel and angular position and absolute velocity percentiles are calculated. The maximum extension during the assembly task is 45 degrees, with an average of 33 degrees (Figure 4). The average velocity is about 1 degree/s (Figure 5). The velocity value is rather low which is mainly because in large part of the assembly task (removing dummy plugs and connecting cables) the wrist has few movements.

The filtered angular position data is also employed to illustrate the power spectrum using FFT and to measure repetitiveness by calculating MPF (Figure 6). The calculated measure shows the rate of about 5 motions/minute (0.08 Hz).

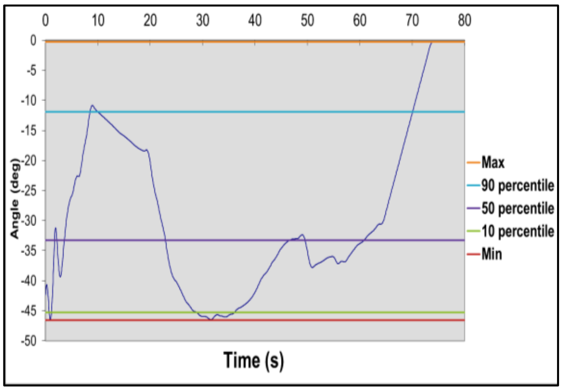


Figure 4. Angular position (deg) vs. time (s) for the right wrist flexion-extension.

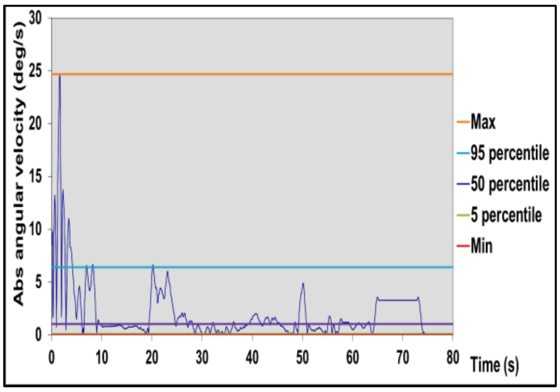


Figure 5. Absolute angular velocity (deg/s) vs. time (s) for the right wrist flexion-extension.

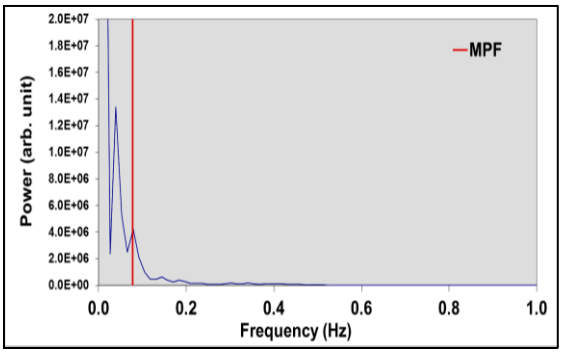


Figure 6. Power spectrum and MPF for the right wrist flexion-extension.

In the next step, the calculated measures are normalized using average and standard deviation of all existing work profiles in the database for the same measure. These normalized values are then used to obtain a weighted profile score (WPS) for each of the 26 work profiles by weighted summing of normalized differences for each measure. The result is a WPS value per each work class profile, showing how similar the simulated task is to each of the work class profiles. Table 1 and Table 2 show the output summary of the results for the simulated task and the closest (minimum WPS) work class profile in the database which is matched with the simulated task. In addition, presumptive complaints and diagnosed disorders based on what is previously recorded in the database are reported. This approach gives that it is assumed that the simulated task is likely to cause 28% of the workers to complain due to experienced wrist pain during the past 12 months of their work period. Also, 3 percent of the workers are likely to be diagnosed to suffer from one or more disorders as listed in Table 2. These results can give an insight to ergonomists and simulation engineers of the need to improve the job conditions in order to prevent work-related musculoskeletal disorders.

Table 1. Output summary from risk measure calculations for the simulated task. Numbers in parentheses are normalized values.

Mean Power Frequency (MPF)	
0.077	Hz
4.65	Motions/minute
Angular position (deg), (+)=flex	
Max	-0.25
10 percentile	-45.28(-1.49)
50 percentile	-33.26(-2.34)
90 percentile	-11.89(-2.29)
Min	-46.55
Absolute angular velocity (deg/s)	
Max	24.69
50 percentile	1.04(-1.59)
Min	0.00

Table 2. Data for the closest work class profile found in ERD and presumptive diagnosis reports. Numbers in parentheses are normalized values.

Work type	Air traffic control		
gender	female		
Percentile	**10**	**50**	**90**
Posture	-44(-1.15)	-28(-1.66)	-4(-1.47)
Absolute Angular Velocity	N/A	2.9(-1.40)	N/A
Complaints (%)	During past 12 months		28
	During past 7 days		17
Diagnosed disorders (%)	One or more diagnosed disorders		3
	Lateral epicondylitis		1
	Medial epicondylitis		1
	Carpal tunnel syndrome		1
	Overused hand syndrome		0

4. Discussion

For several years, ergonomists have identified different risk factors such as posture, joint velocity and repetitiveness to be correlated with WMSD. However, accurate and continuous measurement of these factors is a challenge, e.g. due to the need for technical measurement equipment and knowledge of how to treat the data. Hence, it is common to use simpler observational-based methods, especially in regular industrial applications. Today, DHM tools are providing the opportunity to simulate human motions for complete work sequences, and as a result the tools are able to generate similar data as recorded by direct measurement methods. This study utilizes this opportunity and uses these risk factors along with an epidemiologic database in order to assess the work and predict possible diagnoses.

At the moment, the repetitiveness measure (MPF) is used just for visualization purposes. However, the same approach will be employed to actively consider the effect of repetitiveness on the risk factor measure as soon as proper epidemiologic data is available.

There is a need for further studies to decide the effect (weighting coefficient) of each parameter on the WPS. The possibility to combine and consider different risk factors is a promising approach towards the idea of obtaining one grand score as a measure of presumptive risk. However, further research is needed to validate and calibrate the effect of each parameter.

Accordingly, combination of flexion/extension and radial/ulnar deviation can give a better integrated score when considering wrist joint movements.

At present, motion algorithms in the IMMA tool are reluctant to move the wrist joint if a valid posture using earlier joints in the chain can be found. Consequently, in some cases the generated motion looks unnatural because of this tendency.

Improvements are needed to be made in these algorithms in order to create more natural movements specifically when wrist movements are involved.

5. Conclusion

Digital human modeling tools enable the ergonomists to employ direct measurement methods to analyze human motions during a complete work sequence. A method to analyze wrist joint motions based on its angular position, angular velocity and motion repetitiveness is developed. Using the results from these analyses, presumptive risk factors are predicted by correlating the calculated risk measures to an epidemiologic reference database. A test study was performed using the data from a manual assembly work sequence. The results show that the method can be successfully applied on an industrial case. In addition, presumptive risks and possible diagnoses are predicted based on the similarity of motion characteristics with the motions from other known work class profiles in a database based on epidemiological research.

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