Robert G. Radwin

University of Wisconsin-Madison
Department of Industrial and Systems Engineering
1550 Engineering Drive
Madison, WI 53706
608-263-6596
radwin@engr.wisc.edu

Video Exposure Assessment of Hand Activity

Final Progress Report

Robert G. Radwin, PI

Yu Hen Hu, Co-Investigator

Thomas Y. Yen, Co-Investigator

Mary Lindstrom, Co-Investigator

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List of Terms and Abbreviations

ACGIH	American Conference of Government Industrial Hygienists
F	Frequency
D	Duty Cycle
DC	Duty Cycle
HAL	Hand Activity Level
K (t)	curvature score at time t
m	meter
mm	millimeter
MSE	Mean square error
RMS	Root mean square
ROI	Region of Interest
S	RMS hand speed
s	second
SD	Standard deviation
T	Time or period
t	time
TLV®	ACGIH threshold limit value®
UCB	University of California—Berkeley
UW-Madison	University of Wisconsin-Madison
V	Velocity
$x'(t)$	First derivative of x trajectory vector and corresponds to velocity
$x''(t)$	Second derivative of x trajectory vector and corresponds to acceleration
$y'(t)$	First derivative of y trajectory vector and corresponds to velocity
$y''(t)$	Second derivative of y trajectory vector and corresponds to acceleration

Abstract

This research investigated the feasibility of automatically evaluating the American Conference of Government Industrial Hygienists (ACGIH) Hand Activity Level (HAL) using digital video processing. There is currently no practical instrument for objectively, unobtrusively, and efficiently measuring repetitive motion exposure for evaluating the risk of musculoskeletal injuries in the workplace. Previous methods involve either direct measurements using instruments attached to a worker's hands or arms, or indirect observations. Both instrument and observation methods are mostly limited to research studies and are highly impractical for industry practitioners. The new approach leverages a vast data base of videos and associated exposure data already analyzed manually through collaboration with the University of California—Berkeley (UCB).

A new equation for predicting the hand activity level (HAL) used in the ACGIH threshold limit value® (TLV®), was based on exertion frequency (F) and percentage duty cycle (D). The TLV® includes a table for estimating HAL from F and D originating from data in Latko et al. (1997) and post-hoc adjustments that includes extrapolations outside of the data range. Multimedia video task analysis determined D for two additional jobs from Latko's study not in the original data set, and a new non-linear regression equation was developed to better fit the data and create a more accurate table. The equation, $HAL = 6.56 \ln D \left[\frac{F^{1.31}}{1+3.18\,F^{1.31}}\right]$, generally matches the TLV® HAL lookup table, and is a substantial improvement over the linear model, particularly for F > 1.25 Hz and D > 60% jobs. The equation more closely fits the data and applies the TLV® using a continuous function.

An equation was developed for estimating hand activity level (HAL) directly from tracked RMS hand speed (*S*) and duty cycle (*D*). Since automatically estimating *F* is sometimes complex, HAL may be more readily assessed using S. Hands from 33 videos originally used for the HAL rating were tracked to estimate *S,* scaled relative to hand breadth (*HB*), and single-frame analysis was used to measure *D*. Since *HB*s were unknown, a Monte Carlo method was employed for iteratively estimating the regression coefficients from US Army anthropometry survey data. The equation: $\text{HAL} = 10\left[\frac{e^{-15.87+0.02\,D+2.25\ln S}}{1+e^{-15.87+0.02\,D+2.25\ln S}}\right]$, R^2 = 0.97, had a residual range ±0.5 HAL. The *S* equation superiorly fit the Latko (1997) data and predicted independently observed HAL values (Harris, 2011) better (MSE=0.16) than the *F* equation (MSE=1.28).

A new method for automatically measuring duty cycle (proportion of time exerting force) in repetitive motion jobs was also investigated. A marker-less video tracking algorithm measured hand kinematics (location, velocity and acceleration) in a repetitive laboratory task (Move-Release-Reach-Grasp) for varying hand activity levels (HAL). Trajectory of the hand was identified using spatiotemporal curvature relationships for hand velocity and acceleration and exertion states (Move-Release). The maximum duty cycle error was 7.3%, and on average 2.7 % duty cycle error was achieved. A comparison of HAL ratings against ground truth calculated HAL ratings based on the algorithm had an average error of 0.1, which may be considered negligible.

Section 1. Project Summary

Significant (Key) Findings

1. A new equation for predicting the hand activity level (HAL) used in the ACGIH threshold limit value® (TLV®), was based on exertion frequency (F) and percentage duty cycle (D). The TLV® includes a table for estimating HAL from F and D originating from data in Latko et al. (1997) and post-hoc adjustments that includes extrapolations outside of the data range. Multimedia video task analysis determined D for two additional jobs from Latko's study not in the original data set, and a new non-linear regression equation was developed to better fit the data and create a more accurate table. The equation, $HAL = 6.56 \ln D \left[\frac{F^{1.31}}{1+3.18\,F^{1.31}}\right]$, generally matches the TLV® HAL lookup table, and is a substantial improvement over the linear model, particularly for F > 1.25 Hz and D > 60% jobs. The equation more closely fits the data and applies the TLV® using a continuous function.

2. Since the HAL scale is anchored against speed of motion/exertions and rest pauses, we hypothesized that direct measures of hand speed would more directly measure, and be more closely related to the HAL scale than *F*. An equation was developed for estimating hand activity level (HAL) directly from tracked RMS hand speed (*S*) and duty cycle (*D*). Table lookup, equation, or marker-less video tracking can estimate HAL from motion/exertion frequency (*F*) and *D*. Since automatically estimating *F* is sometimes complex, HAL may be more readily assessed using S. Hands from 33 videos originally used for the HAL rating were tracked to estimate *S,* scaled relative to hand breadth (*HB*), and single-frame analysis was used to measure *D*. Since *HB*s were unknown, a Monte Carlo method was employed for iteratively estimating the regression coefficients from US Army anthropometry survey data. The equation: $\mathrm{HAL} = 10\left[\frac{e^{-15.87+0.02\,D+2.25\ln S}}{1+e^{-15.87+0.02\,D+2.25\ln S}}\right]$, R^2 = 0.97, had a residual range ±0.5 HAL. The *S* equation superiorly fit the Latko (1997) data and predicted independently observed HAL values (Harris, 2011) better (MSE=0.16) than the *F* equation (MSE=1.28). The speed equation fit the Latko data even better than using *F* and *D*. The residual range was less than ± 0.5 HAL.

3. We validated these findings by randomly selecting 30 videos of actual industrial tasks from Harris, et al. (2011), tracked the hand movement to predict HAL, and compared it against the original HAL values observed by the UCSF consortium researchers. The equation for the video predicted HAL v. the observed HAL values had a slope of 0.99 ($p < .001$), R^2 = 0.99.

4. A marker-less video tracking algorithm measured hand kinematics (location, velocity and acceleration) in a repetitive laboratory task (Move-Release-Reach-Grasp) for varying hand activity levels (HAL). Trajectory of the hand was identified using spatiotemporal curvature relationships for hand velocity and acceleration and exertion states (Move-Release). The maximum duty cycle error was 7.3%, and on average 2.7 % duty cycle error was achieved. A comparison of HAL ratings against ground truth calculated HAL ratings based on the algorithm had an average error of 0.1, which may be considered negligible.

Translation of Findings

1. The original HAL lookup table is limited in resolution, omits values, and extrapolates values outside of the range of data. A new equation and table was developed to address these issues.

2. An equation was developed for estimating the HAL rating for the ACGIH Threshold Limit Value® based on hand RMS speed and duty cycle. Speed is more readily evaluated from videos using semi-automatic marker-less tracking, than frequency. The speed equation predicted observed HAL values much better than the F equation.

3. We utilized hand kinematics data to automatically estimate duty cycle (DC). We started with a simple laboratory task consisting of four basic elements, Grasp-Move-Release-Reach. Our aim was to automatically measure exertion time relative to DC (i.e. time elapsed between Move and Release) to calculate DC. The algorithm was used to predict DC for 87 cases. The small average error of 2.7% appears promising. We also calculated HAL based on the predicted duty cycle and RMS speed. The comparison of HAL ratings against ground truth calculated HAL ratings had an average error of 0.1 which

may be considered negligible. Automatic detection of duty cycle from hand kinematic using computer video processing is not only useful for HAL calculation but also may be useful for estimating maximum acceptable exertion levels.

Outcomes/ Impact

Digital video processing may be used to automatically, objectively, and unobtrusively measure repetitive motion exposure. It has several advantages over traditional repetitive motion exposure assessment methods. It is automatic and may be possible to perform the analysis in real-time. I t requires minimum human intervention and discretion. Consequently the analysis is determinate for a given video segment.

Current methods involve either direct measurements using instruments attached to a worker's hands or arms, or indirect human observations. The use of marker-less video is unobtrusive and does not require attaching sensors to the body of workers, which often interferes with the job and possibly movement patterns and exertions. Furthermore such an application might be ported to programmable, camera-enabled mobile devices or tablets. This could lower the instrumentation barrier and make analysis of upper limb work-related occupational hazards more accessible to industry.

Section 2. Scientific Report

2.1 Background

2.1.1 A frequency-duty cycle equation for the ACGIH hand activity level

The American Conference for Government Industrial Hygienists (ACGIH) hand activity level (HAL) was developed for use with normalized peak hand force (NPF) to estimate the threshold limit value® (TLV®), which is a measure of the risk of work related distal upper extremity musculoskeletal disorders (ACGIH Worldwide, 2001). The TLV® is limited to mono-task jobs that can be characterized as repeated exertions separated by periods of rest and that are performed for four or more hours daily.

The HAL scale was first introduced by Latko, et al. (1997) and incorporated into the TLV®. Up to the time of the Latko (1997) study, repetitive work was characterized in terms of cycle time or exertion frequency (Lupajarvi, et al 1978; Silverstein et al. 1987). Latko et al. (1997) proposed a 10-point visual-analog scale that ranged from idle most of the time/ no regular exertions to rapid, steady motion/ difficulty keeping up or continuous exertion. The observers consider exertion frequency, rest pauses and speed of motion according to specified guideline descriptions.

Latko et al. (1997) reported a coefficient of determination of R^2=0.88 for repeated ratings by the same observers after 79 to 118 weeks to show that ratings were consistent over time. Ebersole and Armstrong (2002) analyzed 410 jobs at an automotive assembly plant using two observers recording initial and final rating. Before discussion, HAL reliability was rated as moderate and after discussion, HAL kappa values were rated as good (i.e. 0.75). Ebersole and Armstrong (2006) reported that inter-rater reliability for repetition was high with an interclass correlation coefficient value of 0.71 prior to discussion and 0.87 after discussion. Paulsen et al. (2014) recently reported that HAL inter-rater reliability was a reliable exposure assessment method for 858 cyclic ($\bar{F}$-bar$_w$ = 0.69) and non-cyclic work tasks ($\bar{F}$-bar$_w$ = 0.68).

Previous studies have shown that a cycle time less than 30 seconds was associated with risk of carpal tunnel syndrome and tendinitis (Silverstein et al. 1987; Armstrong et al. 1989; Roquelaure 1997). Latko et al. (1997) reported that HAL ratings were not strongly related to cycle time but were more closely related to hand exertion frequency (R^2=0.58) and duty cycle (R^2=0.53). They argued that frequency and duty cycle were better indicators of the biomechanical burden than cycle time. When the TLV® was proposed by the ACGIH, a need for a lookup table was identified for objectively determining HAL based on job descriptions, and exertion time and frequency measurements.

A linear regression model for HAL as a function of frequency and duty cycle was developed by the ACGIH Physical Agents Committee using the data from 31 of 33 jobs in Latko et al. (1997). The equation was then was used to develop a lookup table for estimating HAL. The 2001 TLV® guideline HAL look-up table (reproduced in Table 1) gives approximate HAL values given estimates for exertion frequency F and duty cycle D, where:

$F = \left(\frac{\text{exertions}}{\text{work time}}\right)$ and $D = 100\left(\frac{\text{work time}}{\text{work time+rest time}}\right)$.

Cells in the table that corresponded to D and F below the range of the observed data were left blank or set to one if the predicted value was less than one. When applying the TLV guidelines, practitioners can ascertain frequency and duty cycle information using instruments, video frame-by-frame analysis or other means.

Table 2.1.1. HAL look-up table published in the TLV® Document (2001)

		Duty Cycle (%)				
Frequency (exertions/s)	Period (s/exertion)	0-20	20-40	40-60	60-80	80-100
0.125	8.0	1	1	--	--	--
0.25	4.0	2	2	3	--	--
0.5	2.0	3	4	5	5	6
1.0	1.0	4	5	5	6	7
2.0	0.5	--	5	6	7	8

Although it offers objective measures of HAL, the look-up table provided in the TLV® (Table 1) has several limitations. The HAL values are rounded to the nearest integer and the table includes only five frequency and five duty cycle values. In addition, HAL values are provided for frequency duty cycle combinations outside the range of the experts' data. An equation that continuously and accurately predicts HAL values along with appropriate ranges for its use would overcome these limitations.

Since its introduction, numerous studies have been published for quantifying repetitive hand motion or for evaluating the efficacy of the TLV® for estimating risk using the HAL scale based on observational or table look-up methods. Observational methods for measuring HAL were employed by Latko et al. (1999), Franzblau et al. (2005), Gell et al. (2005), Violante, et al. (2007), Harris, et al. (2011), Garg, et al. (2012), Bonfiglioli (2013), and Kapellusch et al. (2013). Video frame-by-frame analysis was used by Bao, et al. (2006). Both observational and video methods were employed by Wurzelbacher et al. (2010) and Burt, et al. (2011).

Whether estimating HAL using the observational rating scale or the TLV® lookup table, a positive relationship between HAL and risk of hand and wrist musculoskeletal disorders was established. Significant relationships were found between the TLV® action limit and elbow/forearm tendonitis and carpal tunnel syndrome (CTS) in a cross-sectional study of 908 workers from seven different job sites (Franzblau et al., 2005). Werner et al. (2005) investigated predictors of upper extremity discomfort in a longitudinal study involving 501 industrial and clerical workers over 5.4 years, and found significant increases in musculoskeletal pain were associated with exceeding the TLV® (Odds Ratio = 2.14). A longitudinal study of workers from ten diverse manufacturing facilities and followed monthly for 6 years, found that the TLV®, when treated as a continuous variable, was predictive of increased risk of carpal tunnel syndrome (Garg, et al., 2012), predicted increased risk for carpal tunnel syndrome while controlling for obesity and job strain (Burt, et al., 2013), and that the TLV® showed a statistical trend of association with increased risk of flexor tendon entrapment of the digits using the ACGIH limits (Kapellusch et al., 2013). Armstrong et al. (2006) suggested that the TLV® action limit might be lowered, particularly for surveillance purposes or if other risk factors are observed.

Recent advances allow HAL to be calculated directly using automated video analysis that employs semi-automatic marker-less tracking to measure frequency and duty cycle (Chen et al., 2012). The video-based direct exposure assessment method was demonstrated as promising in a simple laboratory simulation of a hand load transfer task. Such an approach is objective, unobtrusive and does not require attaching sensors to the body of workers, and suitable for a real-time, direct reading exposure assessment instrument for HAL. Automated methods for measuring HAL would benefit from a continuous and accurate equation for calculating HAL directly from the measured parameters.

The Latko et al. (1997) data is reproduced in Table 2.3.1 for the 33 jobs that were rated by a team of expert raters. These jobs are described in Latko (1997) for HAL ranging from 1 to 9. Latko had each job rated by the observers (HAL Rating Time 1), and again by the same team a week later (HAL Rating Time 2). These ratings and their average are shown for each job in Table 2.3.1.

Latko et al. (1997) averaged the observable recovery time across five or more cycles. The time spent in recovery was defined as time in which the busiest hand in the cycle "was not holding, manipulating, triggering, pushing, pulling, or otherwise handling an object." The average recovery time was divided by the average time spent "performing operations" on one unit of product (the cycle time) to yield an average percent of time spent in recovery. The remaining integer percent (100-R) was reported as duty cycle *D*.

We first determines D estimates for two additional jobs from Latko's study that were not included in the original data set. Next an equation is developed that more accurately predicts the 33 Latko et al. (1997) HAL values as a function of F and D. Finally the equation is compared to the TLV® HAL table and a new look-up table is presented.

2.1.2. A hand speed and duty cycle equation for estimating the ACGIH hand activity level rating

The American Conference of Government Industrial Hygienists (2001) Threshold Limit Value® (TLV®) for Hand Activity Level (HAL) rating originates from Latko et al. (1997) where 33 jobs were estimated by a team of expert raters on a 10-point visual analog scale based on hand speed and rest pauses. It may also be determined from a lookup table, which is part of the TLV® by measuring exertion frequency (F) and percent duty cycle (D) where:

$F = \left(\frac{\text{exertions}}{\text{work time}}\right)$ and $D = 100\left(\frac{\text{work time}}{\text{work time+rest time}}\right)$.

Conventional methods for ascertaining the HAL rating for a job depend on a trained observer viewing workers performing the job on site or observing a video of the job off site. The process is often labor intensive and there may be differences in ratings between observers. An automated analysis of the job would be more objective and less obtrusive and may be suitable for a real-time, direct reading exposure assessment instrument for HAL rating. Such an approach depends on direct measurements of hand movements during actual work.

Repetitive motion derives from the cyclical nature of manual work (Radwin and Lin, 1993). Repetition can be described using traditional industrial engineering work methods to identify the fundamental movements and exertions required to perform a job (Armstrong, Radwin and Hansen, 1986). The time required to perform a task can be determined directly through time study or predetermined time systems, and thus the frequency can be estimated from the period of fundamental elemental times. Repetitive motion can also be quantified by measuring movements and exertions.

A variety of electronic instruments for measuring human kinematics of the upper limb, such as electrogoniometers, have previously been used to quantify motions of the hand and wrist for different attributes of work using direct measurements (Buchholz & Wellman, 1997; Jonsson & Johnson, 2001; Schoenmarklin and Marras, 1993; Marshall, Mozrall, & Shealy, 1999). These measurements were used for evaluating hand kinematics, such as speed and acceleration, as well as evaluating repetition. Several studies have attempted to automate the analysis of repetitive motion measurement of in the workplace (Bhattacharya, et al., 1999; Person, Hodgson, & Nagy, 2001). Spectral analysis of electrogoniometer data was proposed as an efficient method for quantifying repetitive motion frequency that agreed closely with observational analysis and was more precise (Juul-Kristensen, Hansson, Fallentin, Andersen, & Ekdahl, 2001; Radwin & Lin, 1993; Yen & Radwin, 2000a). Radwin and Lin (1993) found that single frequency motions were directly related to motion frequency but more complex activities often had multiple frequency components. Radwin et al. (1994) devised an approach analogous to a sound level meter using frequency-weighted filters based on psychophysical data for equivalent discomfort levels resulting from repetitive movements of different amplitudes and frequencies (Lin & Radwin, 1998a, 1998b; Lin, Radwin, & Snook, 1997).

Both observations and direct measurements are mostly limited to research studies and are often impractical for industry practitioners. Compared to instruments, indirect observation lacks precision and accuracy, is not suitable for long observation periods, and requires considerable analyst time (Lowe, 2004). Alternatively, attaching sensors on working hands is time consuming (Yen & Radwin, 2000b), and sensors may interfere with normal working operations. Not only is instrumentation use resource intensive, but the required technical knowledge often makes this approach inaccessible to practitioners. Considering these limits, recent protocols for musculoskeletal research often involved observation (Bonfiglioli, 2013; Burt, et al., 2011; Garg & Kapellusch, 2009; Garg, et al., 2012; Harris, et al., 2011; Kapellusch et al., 2013; Wurzelbacher et al., 2010).

Radwin, et al. (2014) developed an equation for estimating HAL based on measurements of *F* and *D* using data from Latko, et al. (1997) in order to continuously predict HAL values consistent with the TLV® look-up table. The equation:

$$HAL = 6.56 \ln D \left[\frac{F^{1.31}}{1+3.18\,F^{1.31}}\right] \qquad \text{(Equation 1)}$$

more accurately predicted the Latko et al. (1997) data, particularly for $F \geq 1.25$ Hz and $D \geq 60\%$ jobs. Such an equation can be utilized in an instrument for quantifying F and D to directly measure HAL.

It was recently demonstrated for stereotypical laboratory hand transfer tasks that HAL can be calculated using automated video analysis that employs semi-automatic marker-less tracking to directly measure *F* and *D* (Chen et al., 2013). A cross correlation-based template-matching algorithm was programmed to track the motion trajectory of a selected region of interest over successive video frames for a single camera. Automatic measures of *F* however are challenging particularly when repetitive motion becomes more complex than simple cyclical motion patterns involving fundamental frequencies of motion and harmonics. Cyclical motion patterns are more easily identified for stereotypic motion but becomes more challenging for more complex motions that may not originate and terminate at the same location.

Since the HAL scale is anchored against speed of motion/exertions and rest pauses, we hypothesize that measures of hand speed would more directly measure and be better related to the HAL scale than *F*. In the current study we develop a new equation for computing HAL directly from tracked hand *S* (*S* equation) and D rather than relying on estimates of *F* (*F* equation) for an automated instrument to directly measure HAL.

2.1.3. Measuring Duty Cycle Using Automated Video Processing

Duty cycle (DC) is one of the primary measures used for evaluating repetitive exertions, muscle fatigue, and manual materials handling tasks (Rohmert 1973a and 1973b, Moore and Garg, 1995, Wood at al. 1997, Latko at al. 1997, ACGIH Worldwide, 2001, Moore and Wells 2005, Iridiastadi and Nussbaum, 2006, Potvin 2012). It is defined as the percentage of time spent in actual task-related activities, and is typically calculated as the exertion time divided by the total time spent doing the task, including rest periods. The DC has become an important measure for quantifying work activity and manual exertions in the workplace.

Latko at al. (1997) introduced a method for quantifying repetitive hand motion, the hand activity level (HAL), which is related to DC. The HAL scale was incorporated into the American Conference for Government Industrial Hygienists (ACGIH) threshold limit value (TLV) for evaluating the risk of work related distal upper extremity musculoskeletal disorders (ACGIH Worldwide, 2001). HAL is an observational visual-analogue metric which an observer subjectively assesses HAL from 0 to 10 anchored between the “hand idle most of the time and no regular exertions” and “rapid, steady motions/exertion; difficulty keeping up.” The HAL rating can also be evaluated by directly measuring the exertion frequency and DC against a look-up table. Radwin et al. (2014) developed an equation for estimating HAL from these parameters in substitution of the TLV table. An equation was introduced by Potvin (2012) for evaluating the maximum acceptable exertion level, also based on DC.

Common ways for measuring DC include time and motion studies, manual video coding, observational methods, and self-reports. Among these, times studies and video coding are the most accurate, whereas observations and self-reports lack consistency and reliability (Fan 2014). Bao et al. (2006) observed disagreement between observer rated frequency-DC estimates and detailed time study analyzes. In another study, Garg and Kapellusch (2011) discuss the lack of consistency between the methods of evaluating HAL, from observer rated assessment and table look-up values, and address the need for a consistent method of evaluation. Kapellusch at al. (2013) state a similar need for a robust technique.

Recent advances in computer vision enable HAL to be measured directly using automated video analysis that employs semi-automatic marker-less tracking to measure frequency and duty cycle (Chen et al., 2013). Such an approach is objective, unobtrusive, does not require attaching sensors to the body of workers, and is suitable for a real-time, direct reading assessment. Akkas, et al. (2014) introduced an equation for HAL based on hand RMS speed and DC, suitable for use with hand tracking and measuring speed directly. The current study advances the need for an automatic method to measure DC using marker-less video tracking.

2.2 Specific Aims

1. Develop and refine video processing algorithms for automatically and continuously measuring HAL from standard digital video recordings focused on the upper extremities.

2. Validate computer determined HAL values against values judged by human observers and through multimedia video task analysis.

2.3 Methodology

2.3.1 A frequency-duty cycle equation for the ACGIH hand activity level

Using the 33 job descriptions in Latko's study, corresponding figures in Latko et al. (1997), jobs numbered 31 and 32 without duty cycle information were identified as the two handle assembly; riveting jobs in a fiber drum manufacturer both of which have an average HAL of 8.5. These jobs have high frequencies (1.43, 1.67) and low cycle times (1.4, 1.2 seconds). Digital methods were required to find the percent recoveries for both jobs.

The Latko videos of Jobs 31 and 32 were digitized and single frame analysis was conducted utilizing multimedia video task analysis (MVTA, Yen and Radwin, 1995) in order to obtain the previously unavailable recovery time data. The video frame-rate was 30 fps. This allowed frame-by-frame identification and analysis of hand load for the short cycle time jobs. The analyst looked at a sequence of frames to determine whether it was an active exertion.

The motion classifications and definitions from Latko et al. (1997) were used to label active and recovery segments for both jobs. Hand exertions of the most active hand were observed for at least five cycles of the job and averaged. Recovery time was defined as periods when the hand was not holding, manipulating, triggering, pushing, pulling, or otherwise handling an object, and included times when the hand was completely idle, resting upon an object for voluntary support, moving freely, or reaching for an object. These values were divided by cycle time to obtain percent recovery time within the cycle. After confirming the frequency across various cycles throughout the entire video, nine cycles of each job were used to calculate duty cycle. These values appear in Table 2.3.1

A new model for predicting HAL from F and D was developed by fitting candidate three and four parameter asymptotic growth models using F as the "x" variable and allowing the asymptote and growth rate to vary by various functions of D (Ratkowsky, 1990). A broken line model (two segment linear spline) was also considered. All models were fit using non-linear least squares, a generalization of linear least squares used for fitting models that are non-linear in their parameters. This minimization is an iterative process as there is no closed form solution for non-linear models. The ability of the models to fit the data was evaluated using residual plots.

Table 2.3.1. Data* Used for Calculations in Latko et al. (1997)

Job	Description	Industry	HAL Rating Time 1	HAL Rating Time 2	Average HAL	Frequency (exertions/s) F	Duty Cycle (%) D	Cycle time (s)
1	Inspection	Appliance mfg	0.8	0.4	0.6	0.125	26	8.0
2	Milacron	Fiber drum mfg	1.0	2.0	1.5	0.167	11	30.0
3	Marriage Load	Auto components	1.0	1.0	1.0	0.281	54	71.3
4	Auto Edge Wrap	Auto components	1.8	3.5	2.65	0.338	45	80.0
5	Water Jet	Auto components	2.0	2.25	2.13	0.376	55	122.5
6	Transfer Task	Laboratory	2.2	2.5	2.35	0.167	32	6.0
7	Line Stack	Fiber drum mfg	2.5	4.5	3.5	0.740	31	7.0
8	Ground Wire	Appliance mfg	3.4	6.25	4.83	0.820	71	12.2
9	DC Inspection	Glass/mirror mfg	4.2	4.25	4.21	0.385	26	13.0
10	Silkscreen	Auto components	4.2	5.25	4.73	0.769	86	7.8
11	Rotary	Fiber drum mfg	4.4	6.0	5.2	0.500	74	4.0
12	Hanging Parts	Appliance mfg	4.4	4.5	4.45	0.555	59	9.0
13	Bulkhead	Appliance mfg	4.6	4.0	4.3	0.320	47	53.0
14	Panel Upholstery	Office furniture mfg	4.9	4.75	4.83	0.550	83	150.0
15	Fabric Wrap	Auto components	5.2	6.75	5.98	1.330	74	40.5
16	Transfer Task	Laboratory	5.2	5.25	5.23	0.333	43	3.0
17	Securing Fan	Appliance mfg	5.7	6.75	6.23	1.080	95	12.0
18	Wiring Heat Box	Appliance mfg	5.8	6.75	6.28	0.730	84	12.3
19	Upper Back Panel	Appliance mfg	6.0	6.5	6.25	0.870	100	11.5
20	Rear Console	Appliance mfg	6.4	5.5	5.95	0.667	87	12.0
21	Securing Top Panel	Appliance mfg	6.5	6.75	6.63	0.833	100	12.0
22	Shape Cutter	Glass/mirror mfg	6.6	6.75	6.68	1.050	88	42.0
23	Paint - Visors	Auto components	7.2	7.5	7.35	1.260	90	30.0
24	Paint - Armrest	Auto components	7.2	7.75	7.48	1.110	91	19.0
25	Lid Assembly	Auto components	7.2	7.0	7.1	0.917	95	24.0
26	CAN Sewing	Auto components	7.2	8.75	7.98	1.580	93	48.0
27	Deck Sewing	Auto components	7.4	7.5	7.45	0.568	96	95.0
28	Cup Assembly	Auto components	7.6	7.75	7.68	0.800	92	125.0
29	Ergo. Upholstery	Office furniture mfg	7.9	8.0	7.95	0.814	90	214.0
30	Curler	Fiber drum mfg	8.0	8.25	8.13	1.429	71	3.5
31	Hand Operation 2	Fiber drum mfg	8.0	9.0	8.5	1.430	81**	1.4
32	Hand Operation 1	Fiber drum mfg	8.0	9.0	8.5	1.670	82**	1.2
33	Transfer Task	Laboratory	8.2	8.5	8.35	0.667	61	1.5
	Min		0.8	0.4	0.6	0.125	11	1.2
	Max		8.2	9	8.5	1.670	100	214
	Median		5.7	6.5	6.0	0.740	74	12.3

* Shaded region in the table contains data and statistics not originally published in Table II in Latko et al. (1997).

** Values obtained for this analysis. Not included in Table II in Latko et al. (1997).

A model that fits the data well will produce a residual plot with residuals evenly scattered around zero. The models that produced good fits to the data were then compared using likelihood ratio tests for nested models (models where one is a version of the other with one or more parameters set to zero) and AIC (Akaike 1974) for non-nested models. The AIC is a measure of the distance between the fitted values and the data penalized for the number of parameters in the model. We also sought to find a model that produces fitted HAL values reasonably consistent with the values in the TLV® table in order to provide continuity with previous research and applications that used that table.

2.3.2. A hand speed and duty cycle equation for estimating the ACGIH hand activity level rating

The *S* equation was ascertained using regression analysis on data obtained from the Latko (1997) videos of 33 jobs and their associated HAL ratings, so that the new equation is consistent with the current HAL scale. Since the videos were not calibrated, a method for estimating distances to calculate hand speed was developed based on measuring the worker hand breadth measured in pixels directly from a video frame and statistically estimating speed of motion. The resulting regression equation was then validated using independent videos of jobs and observational HAL ratings from Harris et al. (2011).

The videos for the 33 Latko (1997) jobs were digitized and a contiguous segment of the video was selected in which the most active hand was visible and representative of the overall task. It was not always possible to track the hand over an entire cycle for some jobs that had long cycle times due to camera movement and visual obstructions. In these cases video segments were analyzed when the active hand was visible and was representative of the motions performed in an entire cycle. A description of the 33 jobs, observed HAL, F, D and the video segment lengths analyzed, are summarized in Table 2.3.2.

Because the videos originated from 8mm format analog recordings, quality was often noisy and at times limited in contrast. A procedure was developed for reliably tracking the most active hand using a semi-automatic tracking algorithm backed up by multiple analysts. Video segments were first selected and a region of interest (ROI) centering on the hand was identified. The default dimensions for the ROI were 20 × 20 pixels, but depending on the size of the hand in the video, the analyst adjusted the ROI size. The hand ROI in the selected video segment was tracked using the video-tracking algorithm described in Chen, et al. (2013). After tracking the ROI, two independent analysts reviewed the tracked video frame-by-frame in order to identify any deviations from the actual hand location, and manually corrected the tracked ROI when necessary. An additional analyst reviewed the segments tracked by the other analysts and settled any discrepancies greater than the half of the length of the ROI diagonal by correcting the discrepancy, or averaging both if the differences were less than half of the length of the ROI diagonal.

Hand speed magnitude in the x-y axes was measured from the corrected pixel ROI motion record using the equation: $V_{px,i} = (px_{i+1} - px_{i-1})/\, 2\Delta$, $V_{py,i} = (py_{i+1} - py_{i-1})/\, 2\Delta$ and $V_{xy,video} = \sqrt{(V_x)^2 + (V_y)^2}$ where px is the pixel location on the x axis, py is the pixel location on the y axis and $V_{xy,video}$ is the difference between the pixel location for the previous and following video frame divided by two times the sample rate (since the numerator was two frames apart), which was 1/30 s.

Table **2.3.2:** Data from Latko (1997) and associated RMS Speed and Hand Breadth

	Title	Industry	Avg. HAL	Frequency (*F*, exertions/s)	Duty Cycle (*D*, %)	Analyzed Video (s)	RMS Speed (*S*, mm/s)	Hand Breadth (*HB*, pixels)
1	Inspection	Appliance Mfg	0.6	0.125	26	20	255.3	50.7
2	Milacron	Fiber Drum Mfg	1.5	0.167	11	24	424.2	25.3
3	Marriage Load	Auto Components	1.0	0.281	54	60	291.9	38.9
4	Auto Edge Wrap	Auto Components	2.65	0.338	45	60	437.6	43.5
5	Water Jet	Auto Components	2.125	0.376	55	85	388.3	50.0
6	Transfer Task	Laboratory	2.35	0.167	32	10	508.8	47.4
7	Line Stack	Fiber Drum Mfg	3.5	0.740	31	19	665.9	26.5
8	Ground Wire	Appliance Mfg	4.825	0.820	71	20	580.4	23.0
9	DC Inspection	Glass/Mirror Mfg	4.225	0.385	26	28	697.9	32.5
10	Silkscreen	Auto Components	4.725	0.769	86	17	477.7	34.5
11	Rotary	Fiber Drum Mfg	5.2	0.500	74	20	566.1	35.0
12	Hanging Parts	Appliance Mfg	4.45	0.555	59	17	591.8	41.0
13	Bulkhead	Appliance Mfg	4.3	0.320	47	45	636.0	50.0
14	Panel Upholstery	Office Furniture Mfg	4.825	0.550	83	38	526.5	30.8
15	Fabric Wrap	Auto Components	5.98	1.330	74	25	574.0	35.4
16	Transfer Task	Laboratory	5.23	0.333	43	10	811.0	29.4
17	Securing Fan	Appliance Mfg	6.23	1.080	95	13	538.3	21.6
18	Wiring Heat Box	Appliance Mfg	6.28	0.730	84	17	578.5	22.6
19	Upper Back Panel	Appliance Mfg	6.25	0.870	100	33	502.0	31.4
20	Console Back	Appliance Mfg	5.95	0.667	87	13	629.3	27.6
21	Securing Top Panel	Appliance Mfg	6.63	0.833	100	13	535.5	33.4
22	Shape Cutter	Glass/Mirror Mfg	6.68	1.050	88	40	563.0	33.8
23	Paint - Visors	Auto Components	7.35	1.260	90	48	747.4	54.8
24	Paint - Armrest	Auto Components	7.48	1.110	91	45	710.1	59.5
25	Lid Assembly	Auto Components	7.1	0.917	95	40	739.2	31.8
26	CAN Sewing	Auto Components	7.98	1.580	93	85	806.6	31.6
27	Deck Sewing	Auto Components	7.45	0.568	96	89	668.7	23.0
28	Cup Assemly	Auto Components	7.68	0.800	92	93	779.1	18.7
29	Ergon Upholstery	Office Furniture Mfg	7.95	0.814	90	133	908.2	26.4
30	Curler	Fiber Drum Mfg	8.13	1.429	71	20	1055.0	47.3
31	Hand Op 2	Fiber Drum Mfg	8.5	1.430	81	20	1000.0	21.9
32	Hand Op 1	Fiber Drum Mfg	8.5	1.670	82	20	1142.2	38.0
33	Transfer Task	Laboratory	8.35	0.667	61	10	1288.0	28.9

Speed was first calculated in units of pixels per second and then converted into physical units of millimeters. Since the videos originate circa 1997 and were produced for a different purpose, no provisions were made for scaling the images against a standard unit of distance. A scaling procedure was therefore used based on the US Army (1991) hand breadth anthropometry survey data base. The analyst identified the active hand in each video segment and measured the hand breadth in units of pixels using MVTA software (Yen and Radwin, 1995). Hand breadth was used because of its small coefficient of variation of 0.046 for males and 0.048 for females. Hand speed RMS was calculated using the equation:

$$S = \sqrt{\frac{1}{T}\int_{t=T_{E_1}}^{T_{E_2}} S^2(t)\ dt}$$

Where exertion time $T = T_{E2} - T_{E1}$. This calculation is illustrated in Figure 2.3.1. The calibrated RMS speed (mm/s) is plotted against HAL in Figure 2.3.2.

In order to examine the effect of the variation of hand breadth on the scaled RMS speed and the predicted HAL values, a Monte Carlo method was employed such that a hand breadth in mm for each of the 33 jobs was randomly selected from a normal distribution with mean and standard deviation relative to gender based on the US Army (Greiner, 1991) hand anthropometry survey. The ratio of the randomly generated hand breadth to the measured pixel hand breadth was calculated and RMS speed was scaled to mm/s. A regression equation for HAL was first estimated, and another random set of hand breadth sizes were selected for each of 33 jobs and the equation estimate was repeated. This process was reiterated until all of the average regression coefficients converged to a difference less than 10^{-6} from the previous average.

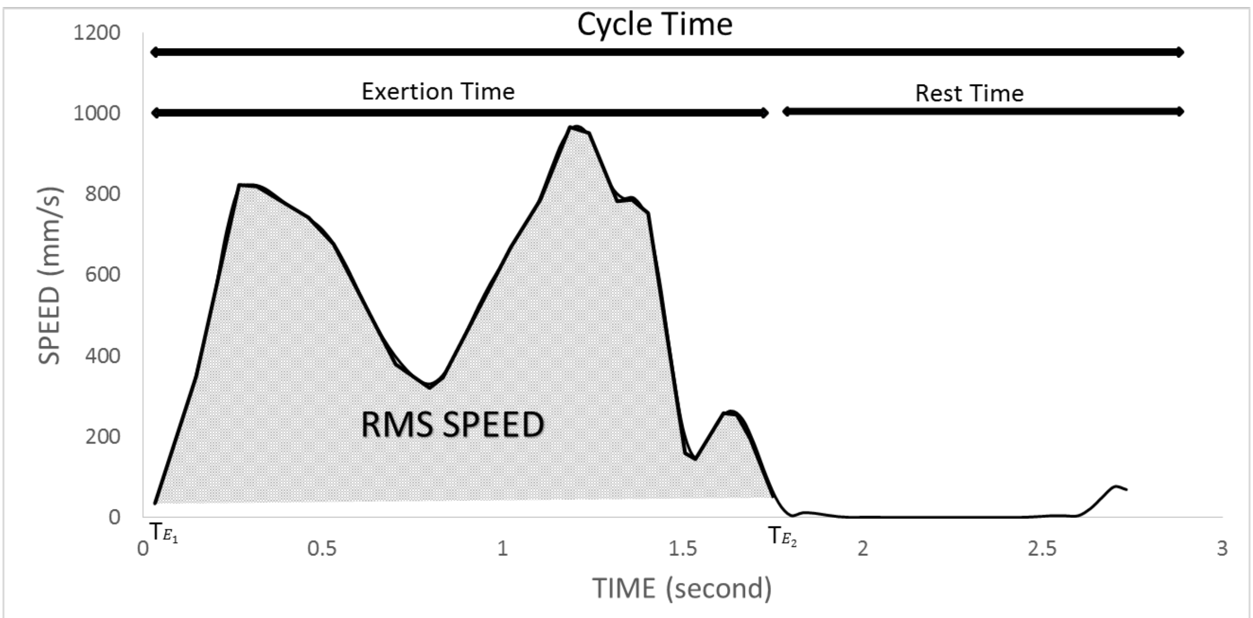


Figure 2.3.1. Representative plot of speed v. time. RMS speed is calculated only during time periods when motion/ exertions are performed.

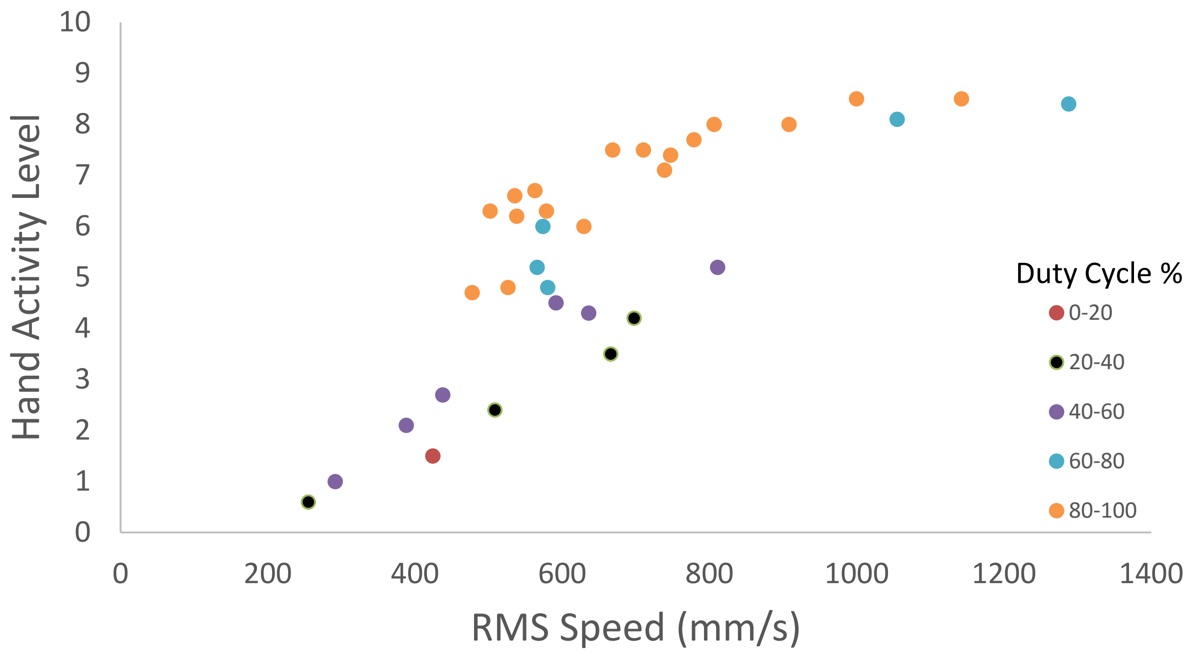


Figure 2.3.2. A plot of Hand Activity Level v. measured Root Mean Square (RMS) speed (*S*) estimated for the 33 jobs from Latko (1997).

A linear regression equation for HAL was tested based on hand *S* and *D* for each set or randomly selected hand widths using the Monte Carlo method described above. The form of the regression equation was:

$HAL = b_0 + b_1 S + b_2 D.$

The predicted HAL value was calculated for each regression iteration for varying *S* and *D*, and the variation in HAL was calculated.

Since the HAL scale is bounded by 0 and 10 and a linear regression can predict beyond that range, we considered an alternative approach. A sigmoidal logit-linear regression equation was fit to the data using a similar Monte Carlo method for estimating hand speed. First the HAL values were rescaled between 0 and 1 by dividing each value by 10. A log transformation of the independent variable RMS Speed was also performed. The logit linear regression equation was in the form:

$$\ln\left[\frac{\left(\frac{HAL}{10}\right)}{1-\left(\frac{HAL}{10}\right)}\right] = b_0 + b_1 \ln(S) + \ b_2 D$$

where HAL is the hand activity level from Latko (1997), *S* is the measured RMS hand speed after scaling, and *D* is the percent duty cycle for each task.

Videos of 30 industrial tasks were randomly selected from Harris, et al. (2011) for validation of the *S* equations. Tasks were excluded if the video recordings had breaks, corruptions or jumps, ambiguous task descriptions and if the task did not have corresponding expert HAL ratings. Based on above criteria, 5 tasks were excluded from the initial 30 random set and 5 new randomly selected tasks were substituted. The HAL range of included tasks were between 2 and 8. These were the same data used by Radwin et al. (2014) for validation of the F equation for HAL.

The videos were randomly assigned to three independent analysts and each task was analyzed by two analysts. The process for video hand tracking to find the hand speed is described above. After hand tracking was completed, an independent analyst confirmed the tracking results. MVTA single frame video analysis (Yen and Radwin, 1995) was performed to measure D for each task. Exertion time and rests period definitions were consistent with Latko (1997).

Exertions were considered a unique application of force by a loaded hand, while rest was marked only when the hand was unloaded. At least 10 cycles of exertions and rest periods for each video segment were marked using MVTA software and the subsequent duty cycles were calculated directly.

2.3.3. Measuring Duty Cycle Using Automated Video Processing

To develop and test an algorithm for automatically measuring DC, we simulated a repetitive motion task in the laboratory. In our simulation, a subject repetitively grasps a ball from one location, moves it to a specified location, releases it, and reaches for another ball. An apparatus (Figure 2.3.3) was fabricated using an electromechanical linear actuator for indexing balls that are obtained in one location and deposited to another for a paced sequence. The participant stands in front of the apparatus, gets a ball at point A, and transfers it to another location. A computer controls the linear actuator ball feed in order to pace the task.

Estimation of duty cycle requires identifying of the time when a hand is loaded and exerting force against an object. In this simulated task, exertions are the time elapsed after the ball is grasped until it is released. The sequence of this task can be described as Move-Release-Reach-Grasp. The time elapsed between Move and Release represents the exertion time, while the total task time cycle time is the time elapsed between Move and the next Move. The DC for the task is therefore the percentage time Move-Release/ Move-Move.

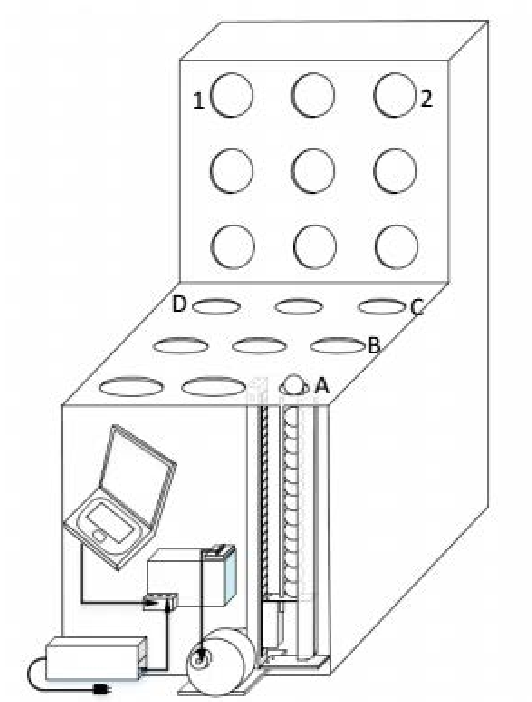


Figure 2.3.3. Task simulation apparatus. Subject grasps ball from A and moves it to locations B, D, 1, or 2 depending on the task.

We recruited 19 university student volunteers (6 males and 13 females) with informed consent. They were video recorded while performing 15 cycles of the task for various frequencies, exertion and rest times that were controlled using an auditory cue (Table 2.3.3). Each subject performed 10 paced task in a session and we randomized the order of tasks. A set of practice sets were provided for each condition. A one minute rest was provided between each condition to prevent fatigue. The task was videoed using conventional video for 30 fps.

The hand movement kinematics was measured using the marker-less video tracking algorithm described in Chen et al. (2013). We identified changes in hand trajectory using spatiotemporal curvature as described in Rao et al. (2002). The spatiotemporal curvature function *K* is defined as:

$$K = \frac{\| \lfloor x'(t)\ y'(t) \rfloor * \lfloor x''(t)\ y''(t)\ 0 \rfloor \|}{\lfloor x'(t)\ y'(t)\ 1 \rfloor^3}$$

which also can be rewritten in the form:

$$K(t) = \frac{\sqrt{y''(t)^2 + x''(t)^2 + (x'(t)\,y'(t) - x''(t)\,y''(t))^2}}{(\sqrt{x'(t)^2 + y'(t)^2 + 1})^3}$$

where K (t) is curvature score at time t, $x'(t)$ is first derivative of x trajectory vector and $y'(t)$ is the first derivative of y trajectory vector. First derivatives $x'(t)$ and $y'(t)$ also correspond to velocities. Similarly $x''(t)$ and $y''(t)$ are second derivatives and correspond to acceleration. This function is sensitive to changes in movement patterns.

Table 2.3.3. Summary of all tasks for experimental design

Location	Frequency (Hz)	Duty Cycle (%)	HAL
A to 1	0.25	65	2.9
A to 1	0.75	60	5.8
A to 2	0.50	20	3.5
A to 2	1.25	47	6.4
A to D	1.25	47	6.4
A to D	1.50	25	5.6
A to C	1.00	15	4.2
A to C	1.50	25	5.6
A to C	1.75	25	5.8
A to B	1.75	25	5.8

A representative spatiotemporal curvature is given in Figure 2, plotted along with corresponding location, velocity and acceleration. The curvature score was used a feature along with location in a decision tree algorithm for identifying states of the repetitive motion task. A set of practice replicates were first used to determine thresholds for each feature in order to train the algorithm. Knowing if the first instance is a Grasp we were able to detect transition states (e.g. Release, Grasp) and calculate the time in between each instance giving us both cycle time and exertion time. As seen in Figure 2.3.4, when a subject is grasping and releasing, the velocity approaches zero and location of hands follows a common pattern in both the *x* and *y* directions. The DC is obtained by dividing exertion time (time elapsed between Move and Release) by total cycle time to calculate the percent time in an exertion.

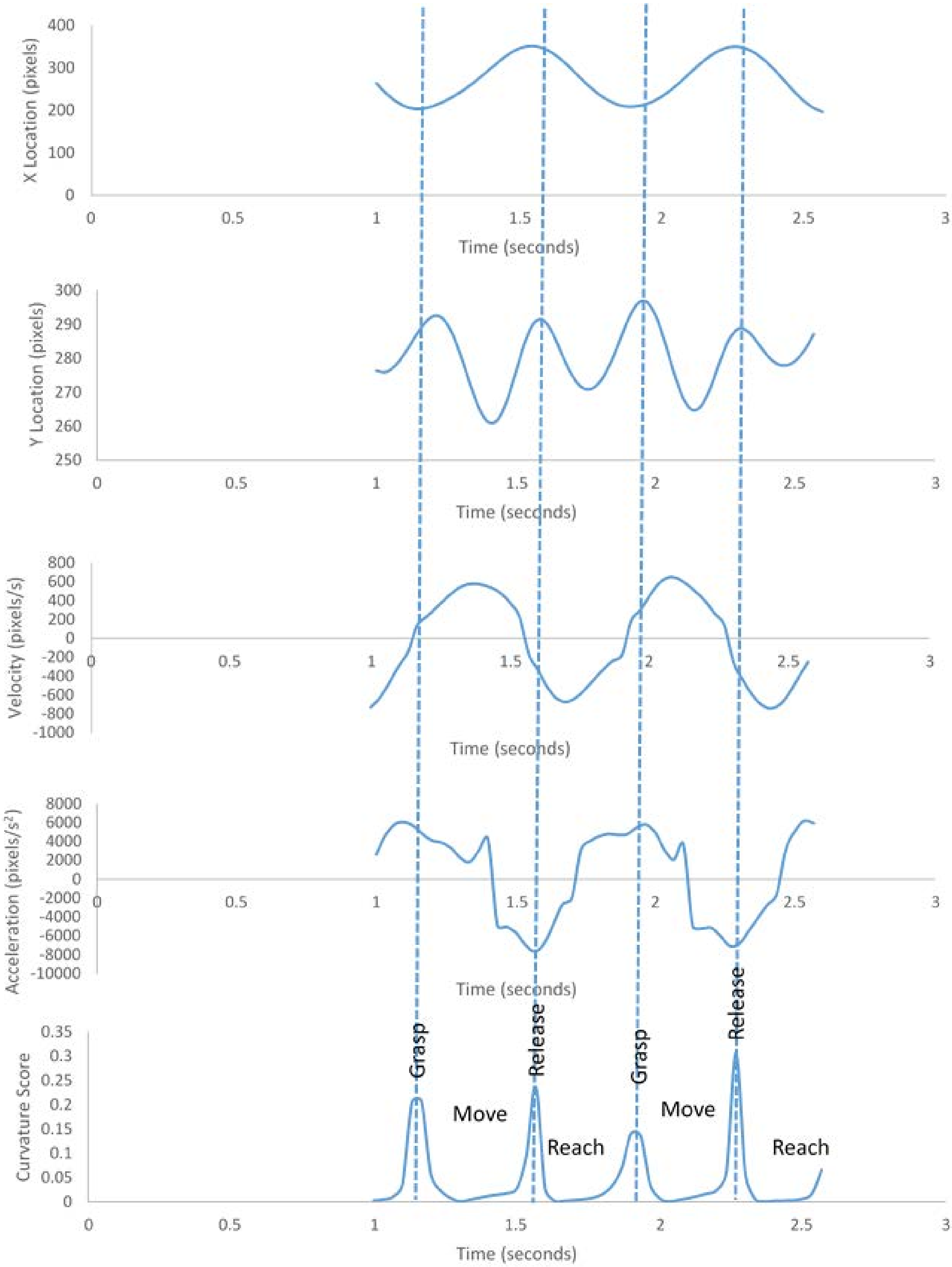


Figure 2.3.4. Typical hand kinematic curves for location, velocity and acceleration aligned with the curvature score.

Three trained analyst extracted ground truth DC measures from videos of each task using singe frame video coding and MVTA software. We then we compared the video DC algorithm outcomes against the MVTA ground truth DC and calculated slope. We also used the tracked hand speed data and estimated DC for calculating HAL using the equation described in Akkas et al. (2014) and compared them against calculated HAL using the ground truth DC data.

2.4. Results

2.4.1 A frequency-duty cycle equation for the ACGIH hand activity level

The newly calculated duty cycle for Jobs 31 and 32 are included in Table 2.3.2. The complete 33 job Latko data set is shown in Figure 2.4.1. Only two of the 33 jobs exhibited frequencies greater than 1.50 exertions/s, and no job exceeded 1.70 exertions/s. Jobs with high frequencies tended to have long duty cycles (Spearman correlation = 0.66). Summary statistics for the job parameters for the full data set was computed and provided in Table 2.

Overlays of the Latko frequency of exertions and duty cycle data (33 jobs) and the TLV® table HAL ranges are shown in Figure 2.4.2. Some of the HAL values in the TLV® table are for frequency and duty cycle combinations not covered by the data, especially for high frequencies that were extrapolated outside of the range of the observed data. The regions corresponding to these table cells are colored grey in Figure 2.4.2. Eight of the HAL predictions are outside the range of the observed frequencies and duty cycles in the original data. In general, predictions from a model that are outside the range of the data are unreliable since there is no way to know if the model is accurate in these regions.

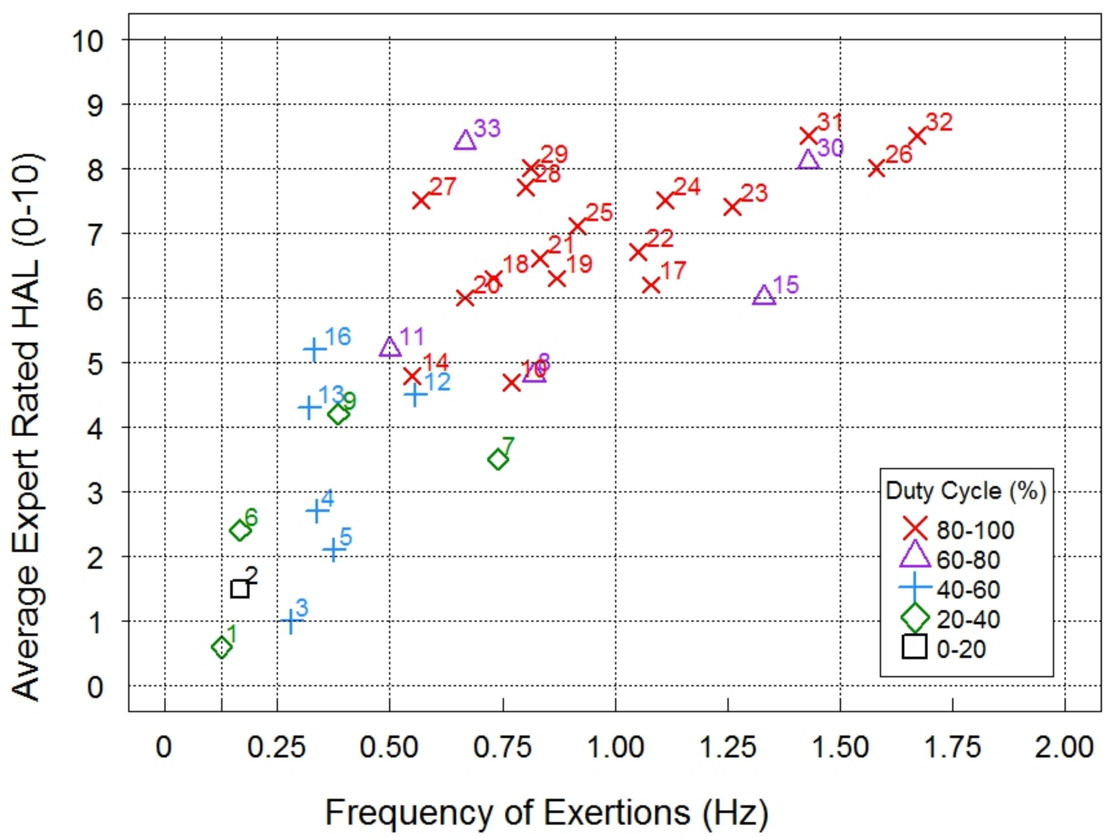


Figure 2.4.1. Complete 33 job data set. Job numbers are shown next to plotted values (including Jobs 31 and 32).

Given the lack of data above 1.5 exertions/s, it is proposed that the frequency row labeled 2 exertions/s in the TLV® table should more accurately be labeled 1.5 exertions/s.

The linear regression model for average rated HAL as a function of period and duty cycle used to populate the TLV table was reproduced using the Latko et al. (1997) data shown in Table 2 (omitting Jobs 31 and 32). That model is

$HAL = 4.31 - 0.636\frac{1}{F} + 0.0339D$ (Equation 1)

where F is frequency in exertions/s, D is percent duty cycle HAL is average HAL. The HAL values predicted by Equation 1 for the 5 duty cycle values in the TLV table are shown in Figure 2.4.3 as curves. The HAL values from the TLV® table are shown as symbols.

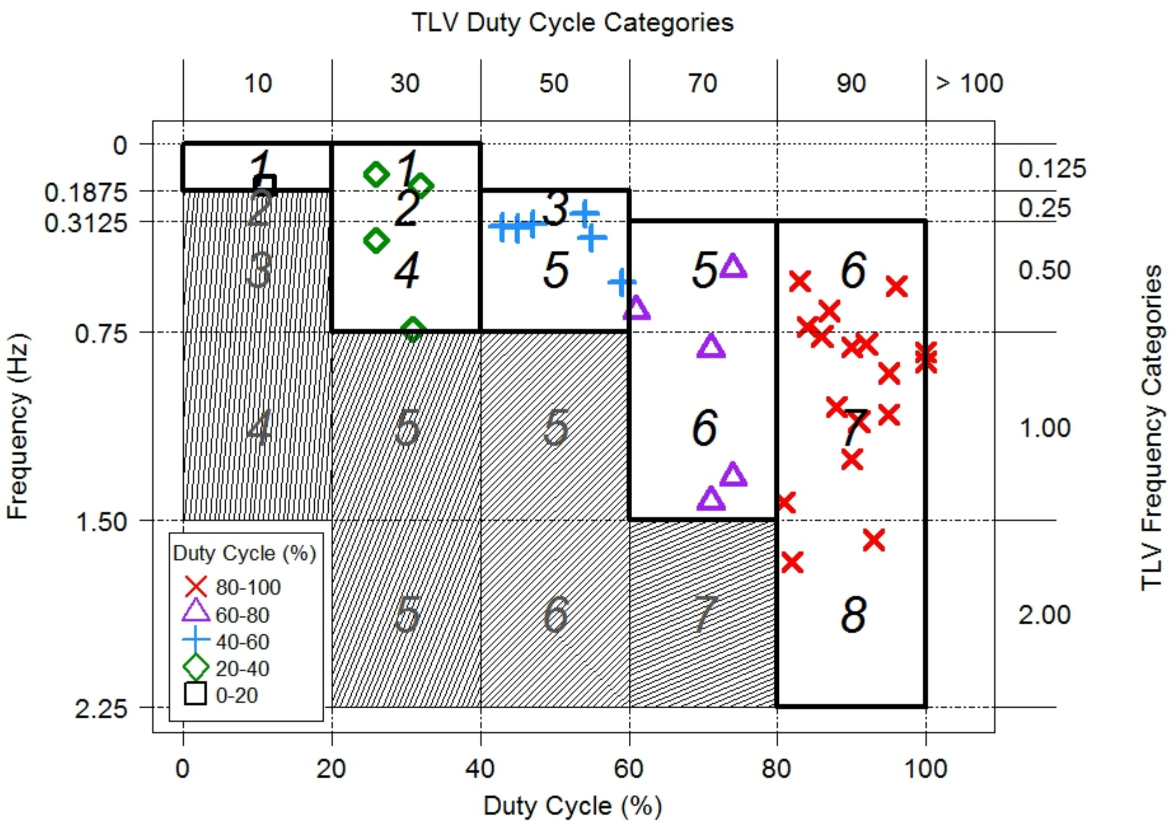


Figure 2.4.2. The Latko data (33 observations) are compared against the HAL values in the TLV Table 1. The plot is oriented similar to the HAL table and areas where table values are provided without data are shaded in grey.

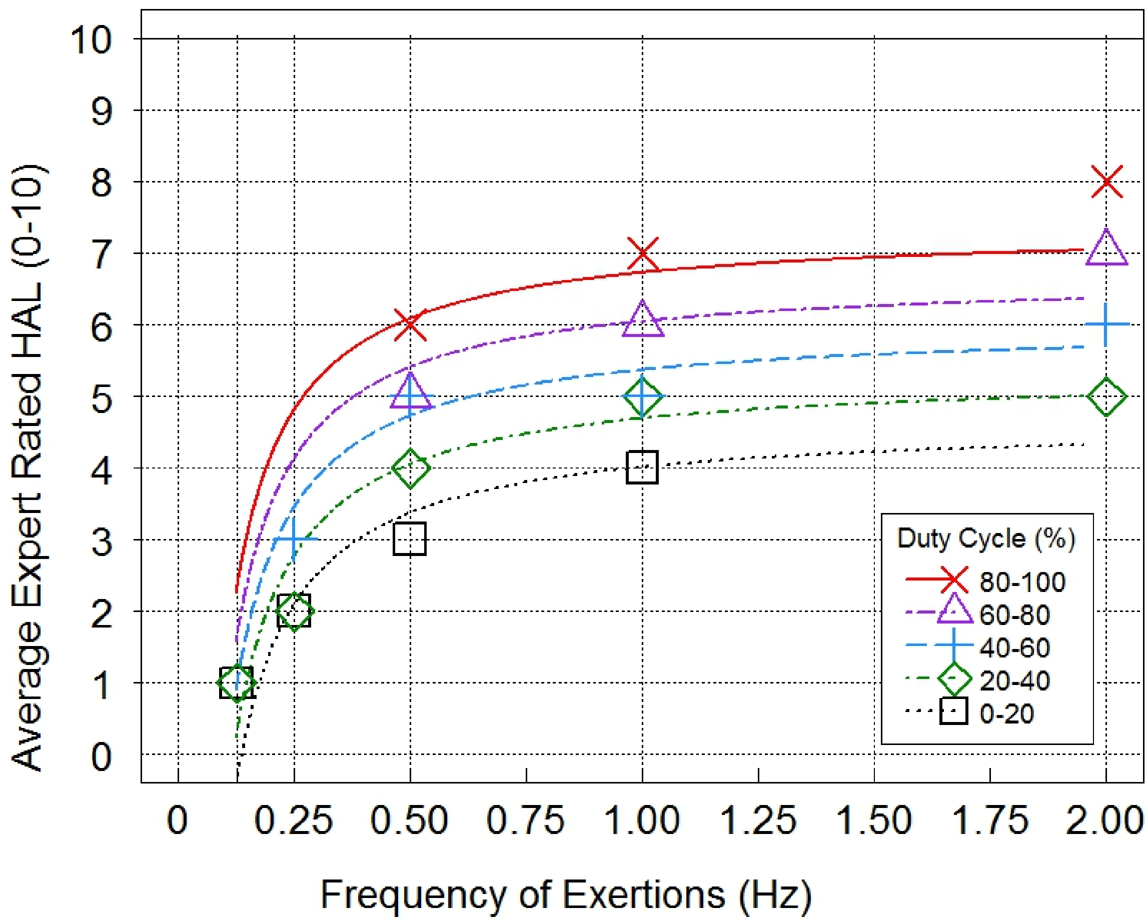


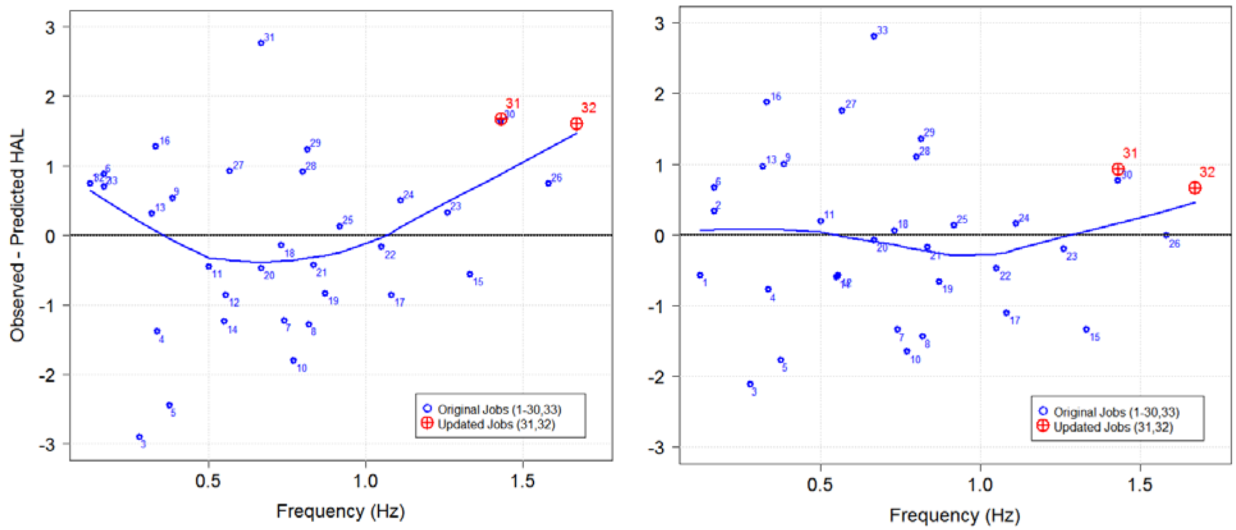
Figure 2.4.3. HAL values predicted by Equation 1 from Table 1 of the TLV. The smooth curves are the fitted values for Duty Cycles of 10, 30, 50, 70 and 90 as a function of Frequency. The symbols are the values from the TLV® Table 1.

It is apparent that the TLV® table HAL values for the higher frequencies and duty cycles have been adjusted from the values predicted by the linear regression equation (Equation 1). The TLV® table values were adjusted upwards from the regression model predictions for F = 2 and D ≥ 50% (as described in the TLV® documentation). The TLV® table also specifies HAL=1 when Equation 1 predicts negative HAL values (i.e. F ≤ 0.125, D < 50). Consequently Equation 1 is not useful as a continuous representation of HAL for measured values of F and D.

The linear regression model in Equation 2 was estimated using the complete 33 job data set:

$$HAL = 4.69 - 0.709\,\frac{1}{F} + 0.0321D \qquad \text{(Equation 2)}$$

The addition of jobs 31, 32 to the data set increased the fitted values at higher frequencies slightly, but the model was still not a good fit to the data. The residuals from this fit are shown in Figure 2.4.4 (a). The residuals for small and large predicted HAL values are all larger than zero indicating that the linear curve under predicts very small and very large HAL values.



(a) (b)

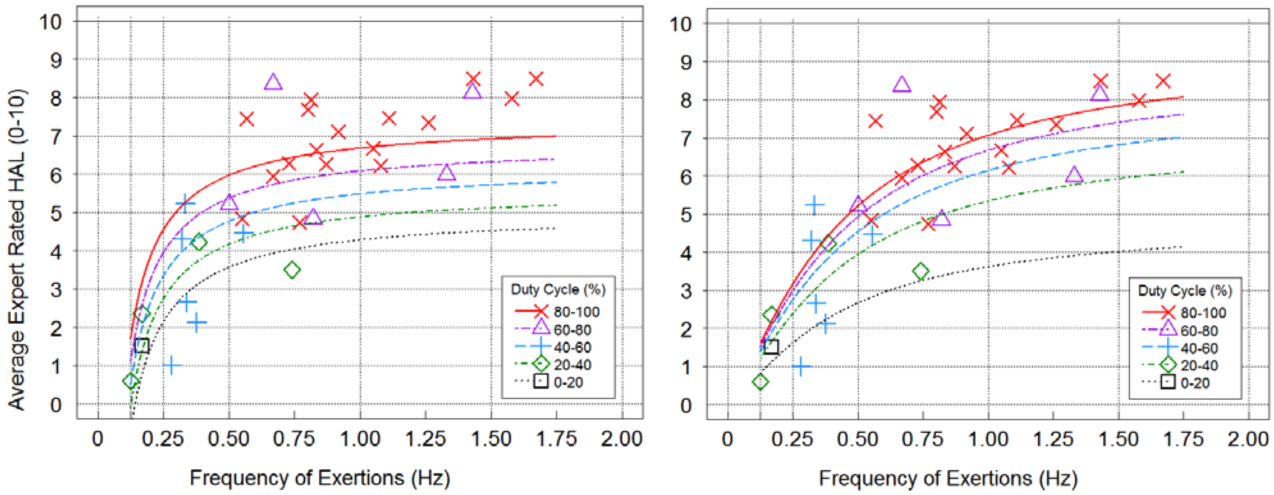
Figure 2.4.4. Residual plot (observed value - predicted value) for the linear model (a) in Equation 2 and the non-linear regression model (b) in Equation 3. The numbers adjacent to data points correspond to the job numbers in Table 2. The curves indicate the trend of the residuals. Ideally these would lie exactly on the residual equal zero line.

We considered other linear and nonlinear functions of frequency and duty cycle to see if a better model could be developed for HAL. The model shown in Equation 3 is the simplest model found that provided both a good fit to the data and closely matched the HAL table (Table 1) values from the Latko (1997) data that are within the range of the data. The predictions from the model are plotted with the Latko data in Figure 2.4.5 (b) and a residual plot is shown in Figure 2.4.4 (b). The residuals for this model indicate a better fit to the data than Equation 2, the estimated residual standard deviation (the typical distance from the data to the fitted model) is smaller for the nonlinear model (1.18 vs 1.31) and the AIC is lower (109.3 vs. 116.2).

$HAL = 6.56 \ln D \left[\frac{F^{1.31}}{1+3.18\,F^{1.31}}\right]$ (Equation 3)

The nonlinear model in Equation 3 closely follows the original TLV® table (Table 1). Differences between Equation 3 predictions and the original TLV® table are plotted in Figure 2.4.6. The adjustments for 90 percent duty cycle made for the original TLV® table are captured by Equation 3.

The TLV® table corresponding to Equation 3 is shown in Table 2.4.3. Values that differ from the current TLV® table (Table 1) are indicated by an asterisk. Ebersole and Armstrong (2002) found that observers were in agreement within one point of the scale 91% of the time. We have reported the predicted HAL values to one decimal place so that these values can be used in calculations such as means and differences and for comparison.



(a)

(b)

Figure 2.4.5. Linear (a) and non-linear (b) regression models with complete Latko et al. (1997) data. The smooth curves are the fitted values for Duty Cycles of 10, 30, 50, 70 and 90 as a function of Frequency.

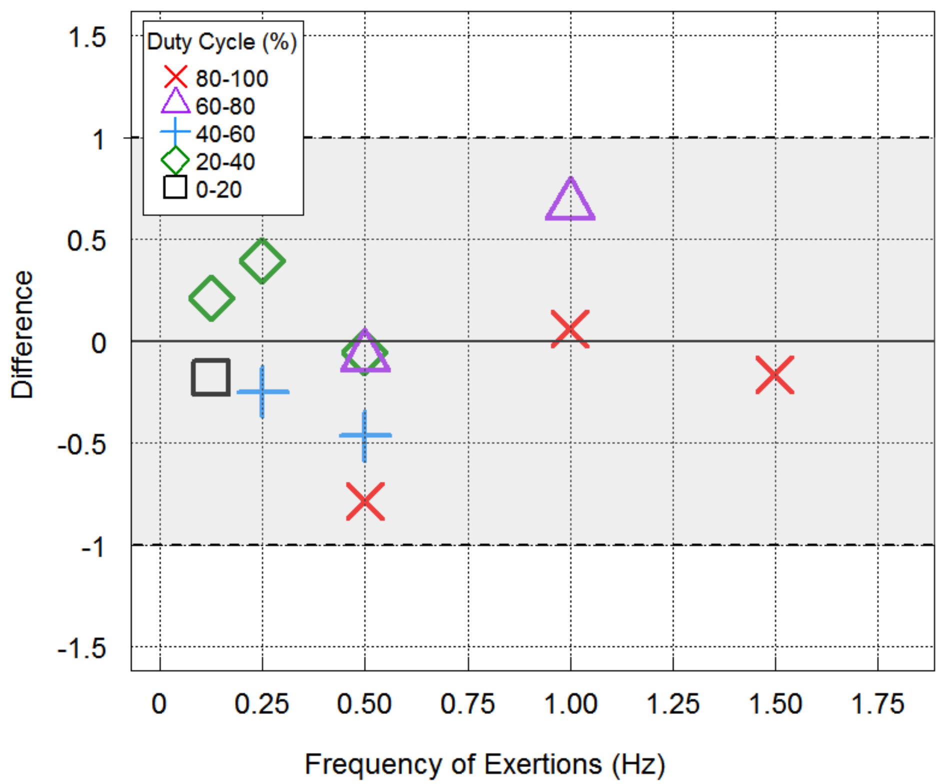


Figure 2.4.6. Differences between the nonlinear model predictions and values in the original TLV® table which are within the range of the data.

Table 2.4.3. HAL look-up table based on Equation 3

		Duty Cycle (%)				
Frequency (exertions/s)	Period (s/exertion)	0-20	20-40	40-60	60-80	80-100
0.125	8.0	0.8	1.2			
0.25	4.0		2.4	2.8		
0.5	2.0		4	4.5	4.9	5.2*
1.0	1.0				6.7*	7.1
1.5**	0.67**				7.4**	7.8**

* Differs from the TLV® table

** Entries not included in the original TLV® table

■ Outside the range of the data

Once calculations are complete HAL values should be rounded to integer values. HAL values were rounded off to the nearest whole number because it was believed that even single decimal values implied greater accuracy and precision than could be supported by the data (ACGIH 2001). In light of recent studies (e.g., Ebersole, et al., 2002; Bao, et al., 2006; Paulson, et al., 2014), single decimal values may facilitate comparing ratings and jobs. Also, single decimal accuracy helps provide insight to the analyst about how much exertion frequency needs to be decreased or recovery time needs to be increased to achieve compliance with the TLV®. It can help the analyst decide if the value should be rounded up or down due to other exposure factors such as posture. A mathematical expression provides estimates of HAL to the nearest 0.1 units will be useful for practitioners.

The TLV® was based on epidemiological and fatigue studies that were available at the time the TLV® was first proposed in 2000 (ACGIH 2001) for estimating combinations of peak force and HAL associated with elevated risk of hand, wrist and forearm work related musculoskeletal disorders. The TLV® for hand, wrist, and forearm work related musculoskeletal disorders recommended an action limit (AL) that should trigger a control program that includes risk factor and health surveillance, education and appropriate control measures as well as a TLV® that should also trigger a control program immediate attention to that exceed the TLV® and to workers performing them.

The availability of an accurate equation for HAL makes it possible to visualize the TLV® guidelines graphically and analytically. The TLV® normalized peak force (NPF) can be expressed as an equation:

$$NPF_{TLV} = 7.8 - 0.78\, HAL$$

Using the expression for HAL given in Equation 3 we obtain the following equation for the TLV:

$$NPF_{TLV} = 7.8 - 0.78\left(6.56 \ln D \left[\frac{F^{1.31}}{1+3.18\, F^{1.31}}\right]\right)$$

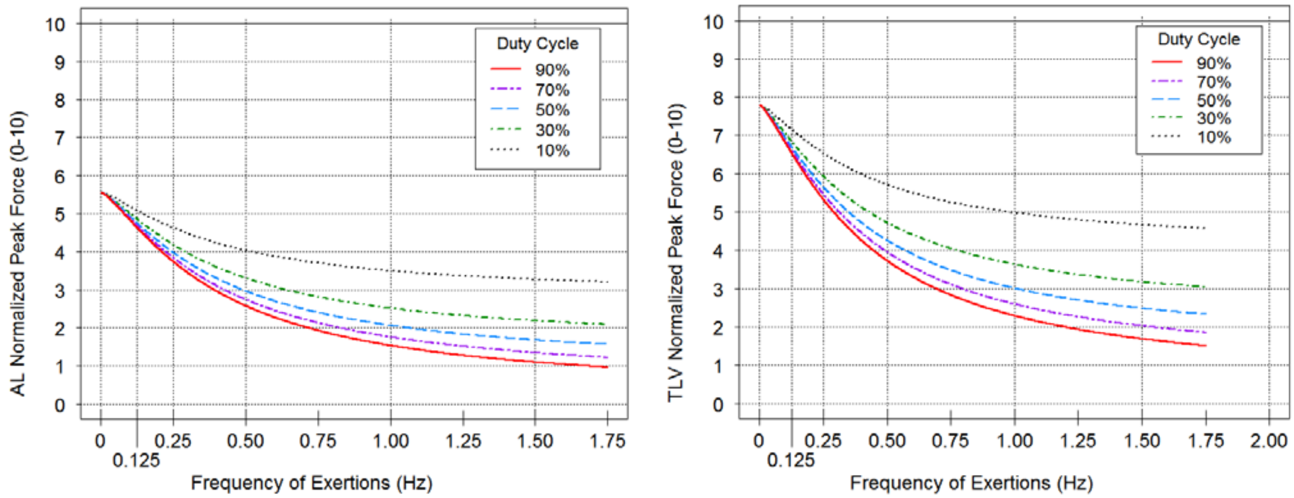
$$= 7.8 - 5.12 \ln D \left[\frac{F^{1.31}}{1+3.18\, F^{1.31}}\right]$$

This limit is shown as a function of frequency for a number of duty cycle values in Figure 8. Similarly, the AL linear equation for NPF is:

$$NPF_{AL} = 5.56 - 0.556\left(6.56 \ln D \left[\frac{F^{1.31}}{1+3.18\, F^{1.31}}\right]\right)$$

and is displayed in Figure 2.4.7 as a function of frequency and duty cycle.

The utility of using this equation in practice may be illustrated in the following example. Consider a task having a



(a) (b)

Figure 2.4.7. Action Limit (a) and Threshold Limit (b) for normalized peak force plotted against frequency and duty cycle values of 10, 30, 50, 70 and 90, according to Equation 3 and the specified AL and TLV functions.

frequency F=0.5 Hz and duty cycle D=90%. Under the HAL look-up table (Table 1) published in the TLV® Document (2001), the job would have a HAL=6. Correspondingly, Equation 3 yields HAL=5.2. Rounding HAL to5 would result in a difference in NPF for the TLV of 0.78 on a 0 to 10 scale, and consequently over-estimate the TLV using the original Table 1.

The current HAL scales, equations, and tables are all based on a relatively small number of observed data that were used in the original studies by Latko et al. (1997). While the proposed equations appear to provide reasonable extrapolations beyond the range of observed data -- they are still extrapolations and should not be relied on beyond the range of the original data. Theoretical models are needed that account for the tradeoff between force, frequency and recovery time. This is a complex multi factorial relationship involving both short term and long term biomechanical and physiological processes that will most likely prove to be nonlinear. Future research may further optimize the equation and complete gaps in the table. Observations of additional jobs over the range of forces and frequencies of the jobs shown in Table 1 should be used to validate the proposed equations until theoretical models are developed and accepted.

The nonlinear equation for HAL (Equation 3) was validated against a set of 30 job video segments (tasks) from Harris, et al. (2011). Tasks were selected at random and deemed eligible for inclusion if the video contained no breaks, corruptions or jumps, had unambiguous task descriptions, and had corresponding expert HAL ratings. Five tasks were excluded from the initial random selection due to video recording jumps or incomplete task depiction in the video record. The resulting random selection included 30 different subjects performing 24 unique tasks, and had expert rated HAL values ranging between 2 and 8.

MVTA single frame video analysis was performed to measure frequency and duty cycle for each task. Exertion time and rests periods in these segments were consistent with Latko (1997). Exertions were considered a unique application of force by a loaded hand, while rest was marked only when the hand was unloaded. At least 10 cycles of exertions and rest periods for each video segment were marked using MVTA software and the subsequent frequencies and duty cycles were calculated directly.

The resulting linear regression (with intercept set to zero) between the equation predicted HAL and the observed HAL values had a slope of 1.04 ($p < .001$) and $R^2 = 0.95$, and is plotted in Figure 2.4.9. Residual analysis for this regression (equation fit-observed HAL) compared against table-predicted HAL values from Table 1 (table value-observed HAL) suggested an improvement for Equation 3 over the original HAL table, especially for high and low HAL values. Table residual values ranged between -3.5 to 2, while all residual values from Equation 3 were contained within the range -2.2 to 2.2. The equation to predict HAL was more randomly distributed and reduced the tendency to under-predict HAL for high frequency and high duty cycle combinations.

Although the equation to predict HAL offers a better estimate than a look-up table, the non-linear regression model contained residuals for some data points that exceeded HAL=2 (Figure 2.4.5b), indicating that the model did not account for some of the variance. A companion paper (Akkas, et al., 2014) explores substituting tracked RMS hand speed for F to automatically estimate HAL using video tracking, and compares the fit when modeling HAL based on F or speed.

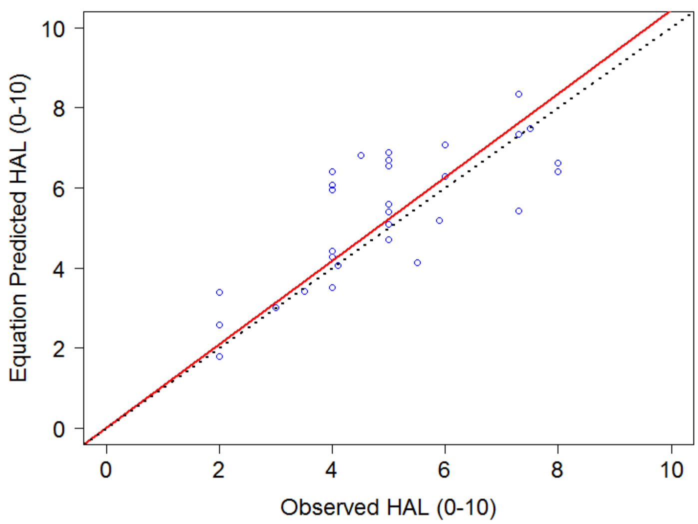


Figure 2.4.8. Validation (N = 30) between expert observed HAL and equation predicted HAL (by Equation 3.)

2.4.2. A hand speed and duty cycle equation for estimating the ACGIH hand activity level rating

A summary of the linear regression equation for HAL is provided in Table 2. The regression coefficients for *S* and *D* were statistically significant for $p<0.05$. Convergence was achieved within 580 iterations using the Monte Carlo process. The average R^2 was 0.82. The model was:

$$HAL = -1.16 + 0.0047\,S + 0.053\,D \qquad \text{(Equation 2)}$$

The upper boundary, lower boundary and means for these predictions are shown in Figure 2.4.9. The maximum difference between the upper bound and lower boundary was 0.25, 0.23, 0.21, 0.20 and 0.19 for duty cycle of 10%, 30%, 50%, 70%, and 90% respectively. The assumption diagnosis plot, residuals versus predicted HAL, indicated no significant variance violation or independence violation and are shown in Figure 2.4.10.

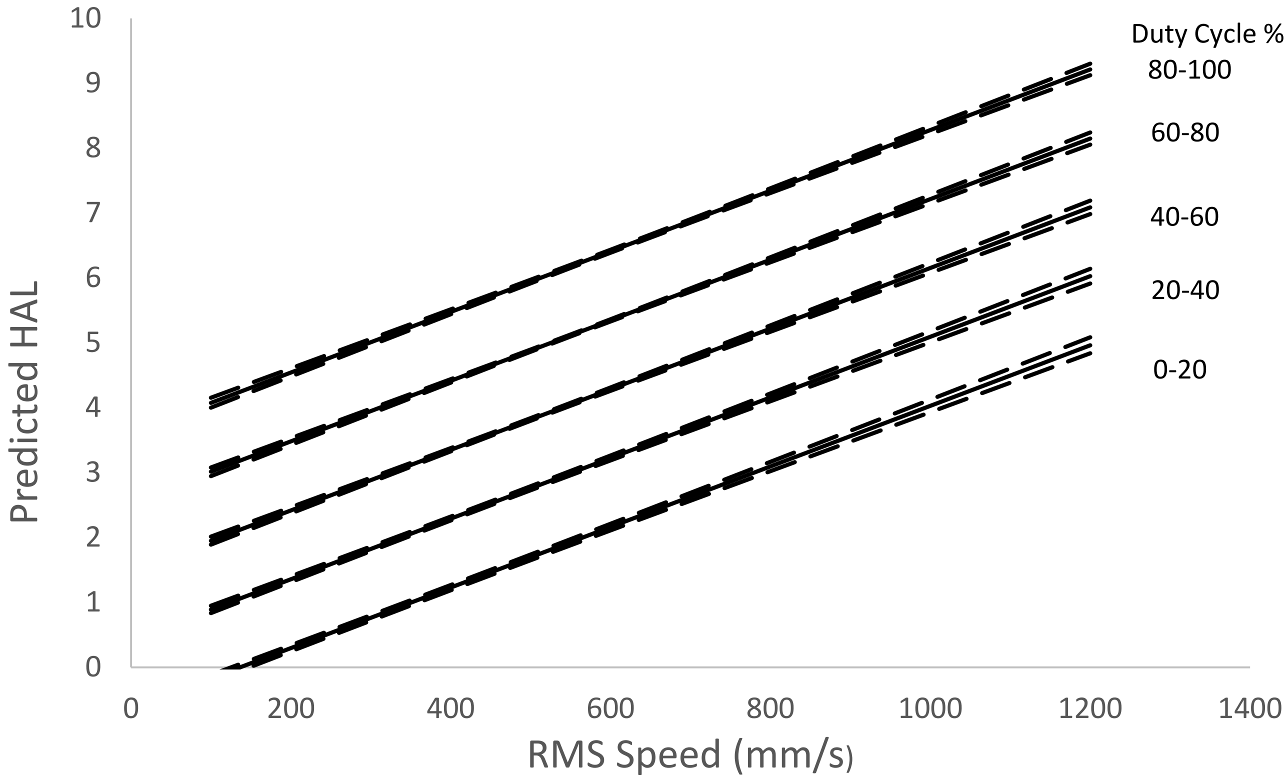


Figure 2.4.9. Plot of the linear equation for predicted HAL as a function of speed (S) and duty cycle (D). The solid line is the average regression line and the dotted lines represent the 0.1 percentile and 99.9 percentile of predicted HALs resulting from the Monte Carol process.

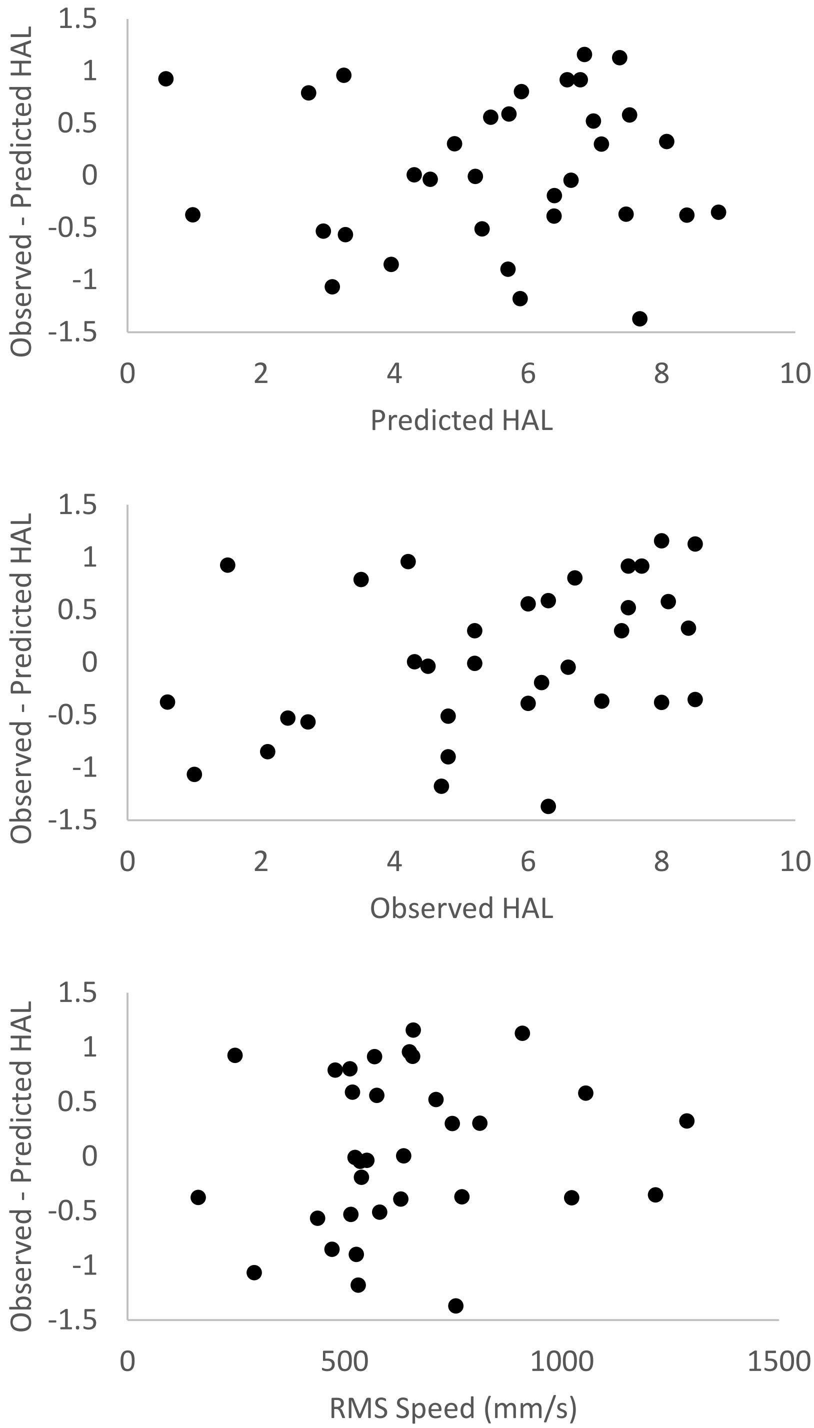


Figure 2.4.10. Linear equation residuals for Observed-Predicted HAL v. Predicted HAL, Observed HAL and RMS Speed.

Table 2.4.4: Summary of the Linear Regression Coefficients from Monte Carlo Simulation for Varying Hand Breadth (N=580)

Variable	Min	Average	Max	Standard Deviation
Intercept	-1.4534	-1.16103	-0.9178	0.08095
RMS Speed (S)	0.0042	0.00465	0.0051	0.00016
Duty Cycle (D)	0.0498	0.05312	0.0562	0.00098
Mean Square Error	0.8569	0.9977	1.1723	

The logit-linear regression equation is summarized in Table 2.4.5 and is plotted in Figure 2.4.11. Regression coefficients for *S* and *D* were statistically significant for $p<0.05$. Convergence was achieved within 238 iterations using the Monte Carlo process. The average R^2 for the logit-linear models model was 0.97 (Naglekeke, 1991, Faraway, 2004). The upper boundary, lower boundary and means for these predictions are shown in Figure 5. The maximum difference between the upper bound and lower bound was 0.26, 0.21, 0.14, 0.13 and 0.19 for duty cycle of 10%, 30%, 50%, 70%, and 90% respectively. A plot of the residuals versus predicted HAL, indicated no significant variance violation and independence violation, and is shown in Figure 2.4.11. The equation was:

$$HAL = 10\left[\frac{e^{-15.87+0.02\,D+2.25\ln S}}{1+e^{-15.87+0.02\,D+2.25\ln S}}\right] \qquad \text{(Equation 3)}$$

The residual range (Figure 2.4.11) was less than ± 0.5 HAL, which was considerably better than the linear regression equation.

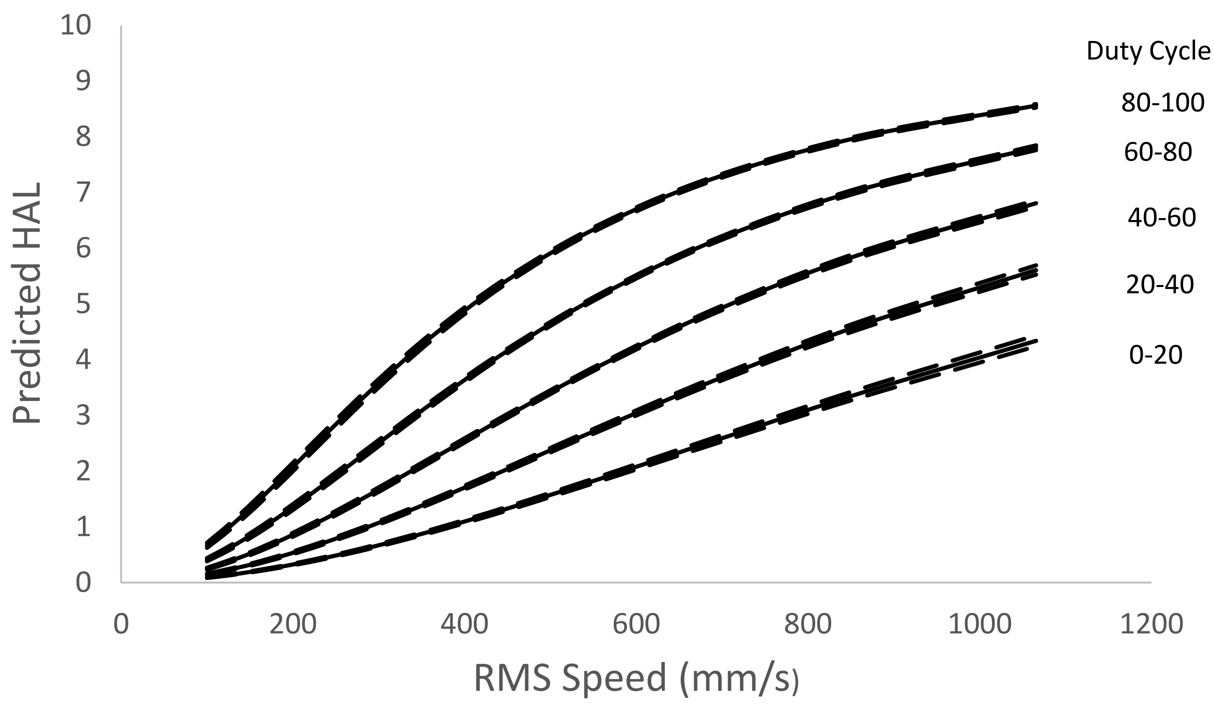


Figure 2.4.11. Plot of the logit-linear equation for predicted HAL as a function of speed (S) and duty cycle (D). The solid line is the average regression line and the dotted lines represent the 0.1 percentile and 99.9 percentile of predicted HALs resulting from the Monte Carlo process.

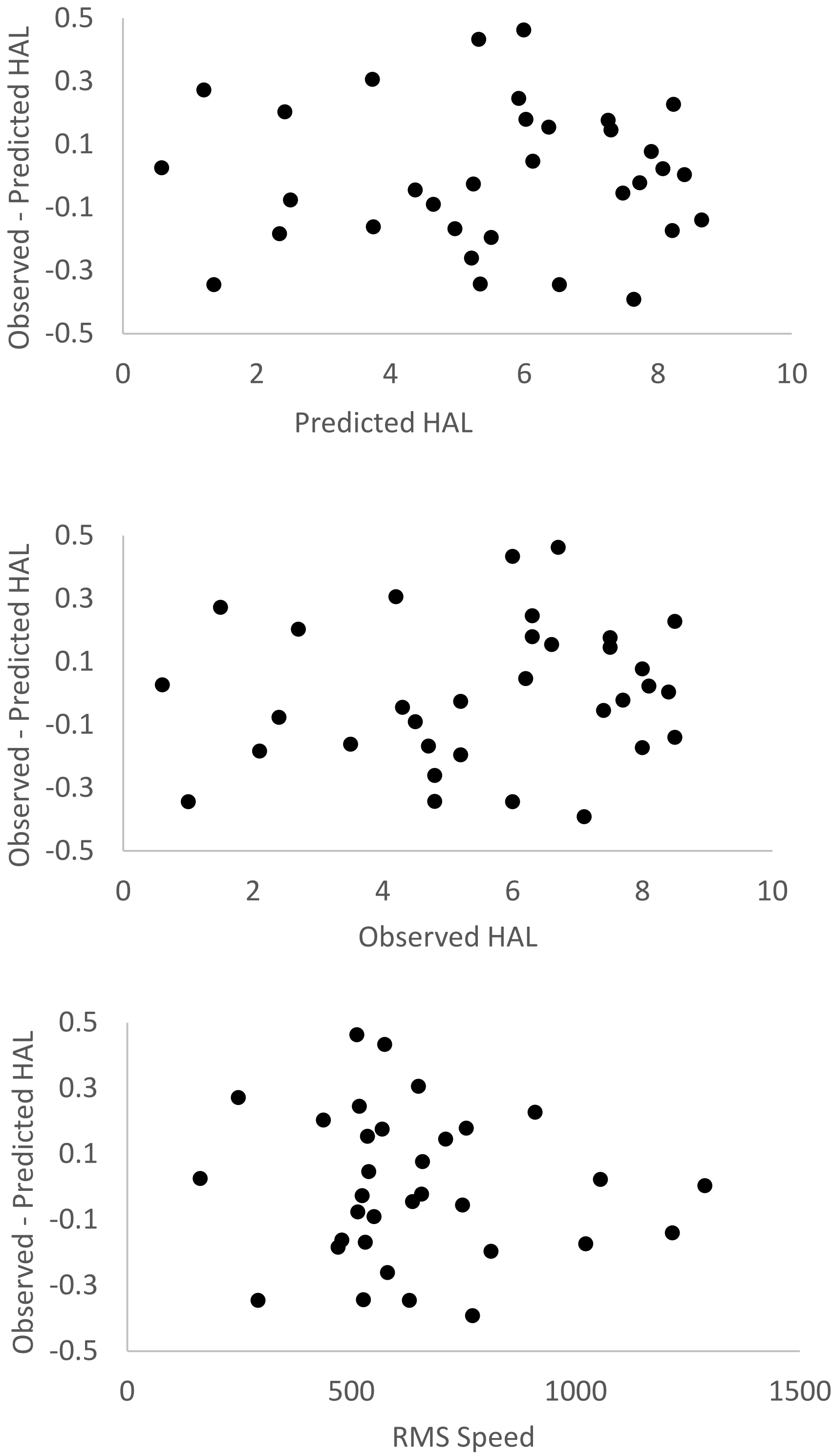


Figure 2.4.12. Logit-linear equation resuuals for Observed-Predicted HAL v. Predicted HAL , Observered HAL and RMS Speed.

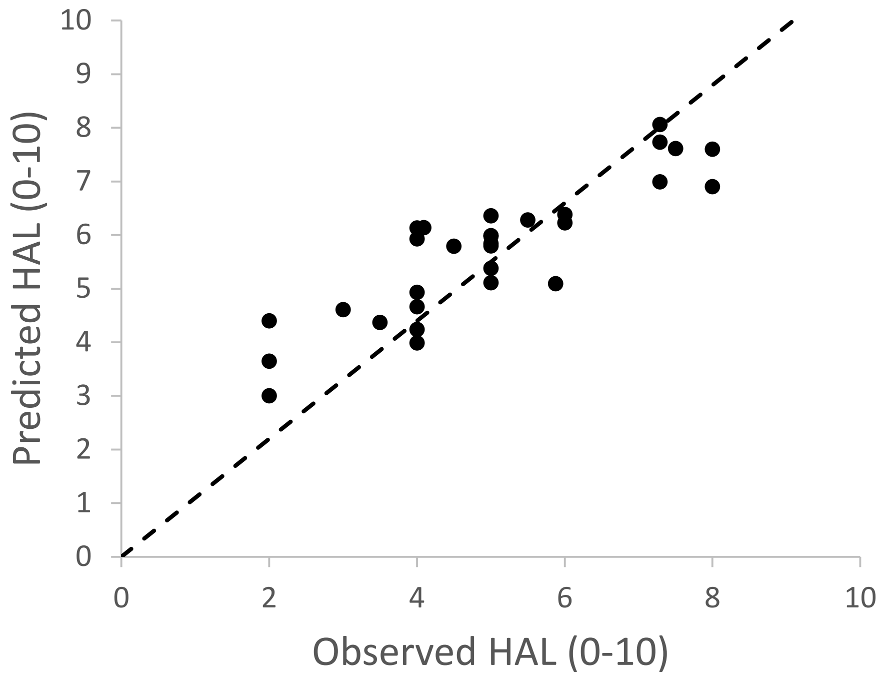
Table 2.4.5: Summary of the Logit-Linear Regression Coefficients from Monte Carlo Simulation for Varying Hand Breadth (N=580)

Variable	Min	Average	Max	Standard Deviation
Intercept	-14.609	-13.492	-12.475	0.304
RMS Speed (S)	1.688	1.861	2.033	0.048
Duty Cycle (D)	0.023	0.026	0.028	0.000
Mean Square Error	0.2907	0.4221	0.5576	

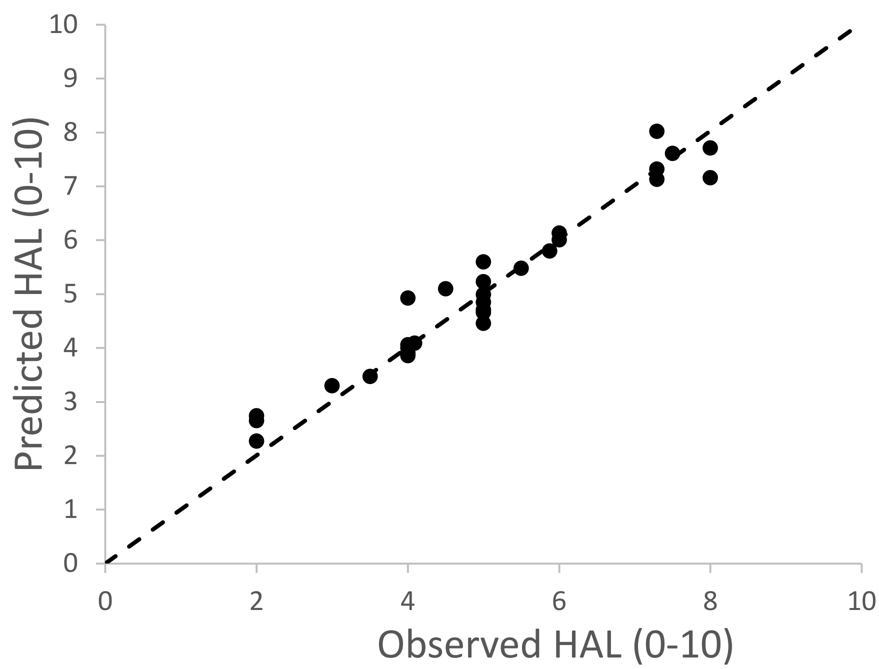
The linear regression (with intercept set to zero) between the linear equation predicted HAL and the observed HAL values had a slope of 0.88 (p<.001), R^2=0.97, and is plotted in Figure 2.4.13(a). The logit-linear equation predicted HAL and the observed HAL values had a slope of 0.99 (p < .001), R^2 = 0.99, and is plotted in Figure 2.4.13(b). The analysis of variance for the F equation and the *S* logit-linear equation are provided in Table 2.4.6. The mean square error for the non-linear regression equation for HAL based on *F* (Radwin at al. 2014) using the same 30 randomly selected tasks found that the mean square error was 1.28. The mean square error for the same data set using the logit equation for *S* and *D* was 0.16.

Table 2.4.6. ANOVA for Validation Regression

Predicted HAL using *F* Equation (Equation 1) v. Observed HAL					
	df	*SS*	*MS*	*F*	*Significance*
Regression	1	784.47	784.48	611.49	<.001
Residual	29	37.20	1.28		
Total	30	821.68			
Predicted HAL using S Linear Model (Equation 2) v. Observed HAL					
	df	*SS*	*MS*	*F*	*Significance*
Regression	1	798.25	798.25	988.23	<.001
Residual	29	23.43	0.81		
Total	30	821.68			
Predicted HAL using *S* Logit-Linear Equation (Equation 3) v. Observed HAL					
	df	*SS*	*MS*	*F*	*Significance*
Regression	1	817.04	817.039	5108.75	<.001
Residual	29	4.64	0.16		
Total	30	821.68			



(a)



(b)

Figure 2.4.13. Predicted HAL plotted against observer rated HAL (From Harris, et al., 2011) for (A) the linear *S* equation (Equation 2) and (B) the logit-linear *S* equation (Equation 3).

2.4.3. Measuring Duty Cycle Using Automated Video Processing

We present summary statistics for ground truth DC, predicted DC, ground truth HAL and predicted HAL in Table 2.4.7. The range for ground truth DC was between 53.7% and 41.8%, with a mean of 48.5%. We calculated error by subtracting each predicted duty cycle from ground duty cycle and taking the absolute value. The greatest error was 7.3% and on average 2.7 % error using above method to predict DC.

Table 2.4.7. Summary of ground truth duty cycle and predicted duty cycle for selected tasks to test the algorithm.

	Ground Truth DC (%)	Predicted DC (%)	Error (%)
Max	53.7	54.2	7.3
Min	41.8	42.9	0.1
Mean	48.5	50.0	2.7
SD	2.7	2.2	1.9
	Ground Truth HAL	Predicted HAL	Error
Max	8.7	8.7	0.3
Min	4.2	4.4	0.0
Mean	6.5	6.5	0.1
SD	1.0	1.0	0.1

Similarly, the HAL range for the task was between 4.2 and 8.7. The maximum HAL error was 0.3 and on average it was 0.1. A comparison of HAL calculated using estimated duty cycle versus HAL using ground truth duty cycle is shown in Figure 3 (R^2= 0.99).

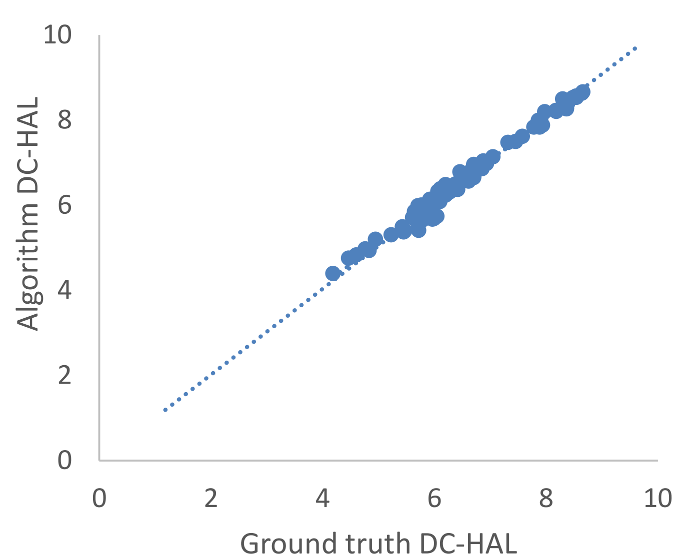


Figure 3. Predicted DC HAL versus ground truth DC HAL.

Discussion

We analyzed videos for the 33 jobs from Latko (1997) in order to find an association between the HAL scale, measured *S* and *D*. We considered estimating HAL using S rather than F because the HAL scale is inherently based on speed. Indeed this is consistent with the HAL scale anchors where HALs of 2-4 are labeled slow motions and HALs of 8-10 are labeled rapid motions. In addition, speed measurement lends itself more readily adaptable to automated processing.

In the linear equation, the significant coefficient for speed of 0.00465 indicates that every 100 mm/s increase in RMS speed increases HAL approximately 0.5 units. Note that the range of speed was 162-1,288 mm/s (Table1). This increase is approximately the same as a 10% increase in D; a 10% D increase yields a 0.53 increase in HAL. However in the logit-linear equation the speed enters the equation with its log taken and the coefficient is 2.25. Since the relationship is not linear, a direct comparison is not possible. However we can provide some examples of how the speed and duty cycle changes affect HAL. When speed is 500 mm/s and there is a 57% duty cycle, the associated HAL value is 3.2 and a 100 mm/s increase in speed will increase the HAL by 0.95. The same amount of increase is gained by 20% increase in duty cycle.

We conclude from the Monte Carlo simulation that hand breadth did not adversely affect the HAL prediction as a benchmark for scaling the hand speed. The use of hand breath was a convenient reference measure that showed little intra subject variation. The variation in HAL based on an average of 238 regressions from a random sampled set of hands showed little difference when normalized to hand breadth. For example, a worker has 355.6 pixels/s measured hand speed and using average male hand breadth (90.4 mm), the speed scaled to 726.57 mm/s yielding HAL of 5.2.

If the worker had the maximum hand breadth in the population, which is 106 mm (US Army, 1991) then the speed will be scaled to 819.3 with HAL of 5.9. On the other hand, if the worker has the minimum hand breadth in the population, which is 77 mm, then speed would be 595.17 with HAL of 4.1. The above case is for extreme cases which is not typical. The 90^{th} and 10^{th} percentile hand breath yields HAL ranges in between 4.7 to 5.4 which gives a maximum difference of 0.5 HAL. Thus an average hand breadth might be used to convert the speed from pixel/s to mm/s for videos when a calibration measure is not available. When videos are made using a reference calibration, the hand speed can be measured directly without the need to use hand breadth.

We validated our findings by using 30 randomly selected tasks from Harris, et al. (2011). The linear models under-predicted observer HAL, especially for the lower levels of HAL. The logit-linear *S* model had the best predictions of observed HAL. The predicted HAL values for the logit-linear *S* equation were consistent with observer rated HALs with mean square error of 0.16. For either model, the *S* equation better predicted observed HAL ratings when compared to the equation based on *F* (Radwin at al. 2014) which had a much greater mean square error of 1.28.

The use of hand speed was actually more consistent with the HAL values obtained from observation than using the frequency of exertion. The logit-linear *S* equation was substantially better (MSE=0.16) than the equation based on *F* (MSE=1.28) using the same 30 randomly selected tasks as shown in Table 4 (Radwin at al. 2014). The current validation only studied 30 randomly selected jobs. Future work should consider a wide range of jobs that vary in frequency, duty cycle and speed.

The development of an accurate equation for estimating HAL ratings should better enable use of automated and objective measurements in practice. While expert observer HAL ratings offer speed and efficiency, use of objective measurements based on worker hand kinematics should provide greater reliability, as well as offering specific engineering aspects of the job that may be addressed for reducing exposures and the risk of musculoskeletal injuries. For instance, a practitioner can use such an equation for quantitatively predicting the benefit of increasing pauses or reducing speed of movements and exertions. Furthermore, automated video analysis may help improve the speed and efficiency of making objective measurements in practice.

We utilized hand kinematics data to automatically estimate DC. We started with a simple laboratory task consisting of four basic elements, Grasp-Move-Release-Reach. Our aim was to automatically measure exertion time relative to DC (i.e. time elapsed between Move and Release) to calculate DC. The algorithm was used to predict DC for 87 cases. The small average error of 2.7% appears promising.

We also calculated HAL based on the predicted duty cycle and RMS speed. The comparison of HAL ratings against ground truth calculated HAL ratings had an average error of 0.1 which may be considered negligible. Automatic detection of duty cycle from hand kinematic using computer video processing is not only useful for HAL calculation but also useful for estimating maximum acceptable exertion levels.
We will next apply the algorithm for actual industrial tasks. More complex tasks will require adding additional states in the algorithm, such as Wait and Hold.

Conclusions

1. Some of the HAL values in the ACGIH TLV® table are for frequency and duty cycle combinations not covered by the original Latko et al. (1997) data, especially for high frequencies.

2. The Latko et al. (1997) data omitted duty cycle for two high frequency jobs (No. 31 and 32), which were not used in creating the TLV® HAL Table. We digitized the original videos and calculated the duty cycles for these jobs. The percent recovery for Jobs 31 and 32 was 81% and 82% respectively.

3. We observed that when the TLV® HAL Table was created, the values for low frequencies and short duty cycles were set to 1, HAL for frequencies of 2 exertions per second were adjusted one unit greater than the original linear model actually predicted, and extrapolated outside the range of the available data.

4. A new equation was developed that provides HAL predictions for all values of duty cycle and frequency within the range of the Latko et al. (1997) data.

5. Given the lack of data above 1.5 exertions/s, it is proposed that the frequency row labeled 2 exertions/s in the ACGIH TLV® table should more accurately be labeled 1.5 exertions/s.

6. The logit-linear *S* equation provides a better fit to the original HAL data (MSE=0.422) than the linear *S* equation (MSE=0.998).

7. A Monte Carlo process demonstrated that hand speed can be acceptably estimated, when a distance reference measure is unavailable, by using the hand breadth measured from the video scaled to a population mean hand breadth (90.4 mm for males and 79.5 mm for females).

8. The equations were validated against a set of 30 task videos of actual workers independently rated on the HAL scale using the observation method. The logit-linear *S* equation best predicted the observer HAL data (slope = 0.99, R^2=0.99). The logit-linear *S* equation provided a better fit to the observed HAL validation data (MSE=0.16) than the linear *S* equation (MSE=0.81), and was substantially better than the linear regression *F* equation (MSE=1.28).

9. Semi-automatic video analysis of HAL would benefit from use of the *S* equation, as well as single frame analyses of industrial jobs.

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