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A hand speed – duty cycle equation for estimating the ACGIH hand activity level rating

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An equation was developed for estimating hand activity level (HAL) directly from tracked root mean square (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 HBs were unknown, a Monte Carlo method was employed for iteratively estimating the regression coefficients from US Army anthropometry survey data. The equation: $\mathrm{HAL} = 10[e^{-15.87+0.02D+2.25\ln S}/(1 + e^{-15.87+0.02D+2.25\ln S})]$, $R^2 = 0.97$, had a residual range ± 0.5 HAL. The S equation superiorly fits the Latko et al. (1997) data and predicted independently observed HAL values (Harris 2011) better (MSE = 0.16) than the F equation (MSE = 1.28).

Practitioner Summary: An equation was developed for estimating the HAL rating for the American Conference of Government Industrial Hygienists 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.

Keywords: repetitive motion; work-related musculoskeletal disorders; exposure assessment

1. Introduction

The American Conference of Government Industrial Hygienists (ACGIH Worldwide 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 percentage duty cycle (D) where

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

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 labour 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 et al. 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 and Wellman 1997; Jonsson and Johnson 2001; Schoenmarklin and Marras 1993; Marshall, Mozrall, and 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 in the workplace (Bhattacharya et al. 1999; Person, Hodgson, and Nagy 2001). Spectral analysis of electrogoniometer data was proposed as

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an efficient method for quantifying repetitive motion frequency that agreed closely with observational analysis and was more precise (Juul-Kristensen et al. 2001; Radwin and Lin 1993; Yen and 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, Lin, and Yen (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 and Radwin 1998a, 1998b; Lin, Radwin, and 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 and Radwin 2000b), and sensors may interfere with normal working operations. Not only is instrumentation use resource intensive, but also the required technical knowledge often makes this approach inaccessible to practitioners. Considering these limits, recent protocols for musculoskeletal research often involved observation (Bao et al. 2006; Bonfiglioli et al. 2013; Burt et al. 2011; Garg and Kapellusch 2009; Garg et al. 2012; Harris et al. 2011; Kapellusch et al. 2014; 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

$$\mathrm{HAL} = 6.56 \ln D \left[\frac{F^{1.31}}{1 + 3.18\, F^{1.31}} \right], \tag{1}$$

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 utilised 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 (ROI) 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 hypothesise that measures of hand speed would more directly measure and be better related to the HAL scale than F. In this 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. Methods

The S equation was ascertained using regression analysis on data obtained from the Latko et al. (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 (HB) 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 et al. (1997) jobs were digitised 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 analysed 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 analysed are summarised in Table 1.

Because the videos originated from 8 mm 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 ROI centring 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 half of

Table 1. Data from Latko et al. (1997) and associated RMS speed and HB.

	Title	Industry	Avg. HAL	Frequency (*F*, exertions/s)	Duty cycle (*D*, %)	Analysed video (s)	RMS speed (*S*, mm/s)	Hand breadth (HB, pixels)
1	Inspection	Appliance manufacturing	0.6	0.125	26	20	255.3	50.7
2	Milacron	Fiber drum manufacturing	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	Fibre drum manufacturing	3.5	0.740	31	19	665.9	26.5
8	Ground wire	Appliance manufacturing	4.825	0.820	71	20	580.4	23.0
9	DC inspection	Glass/mirror manufacturing	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	Fibre drum manufacturing	5.2	0.500	74	20	566.1	35.0
12	Hanging parts	Appliance manufacturing	4.45	0.555	59	17	591.8	41.0
13	Bulkhead	Appliance manufacturing	4.3	0.320	47	45	636.0	50.0
14	Panel upholstery	Office furniture manufacturing	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 manufacturing	6.23	1.080	95	13	538.3	21.6
18	Wiring heat box	Appliance manufacturing	6.28	0.730	84	17	578.5	22.6
19	Upper back panel	Appliance manufacturing	6.25	0.870	100	33	502.0	31.4
20	Console back	Appliance manufacturing	5.95	0.667	87	13	629.3	27.6
21	Securing top panel	Appliance manufacturing	6.63	0.833	100	13	535.5	33.4
22	Shape cutter	Glass/mirror manufacturing	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 assembly	Auto components	7.68	0.800	92	93	779.1	18.7
29	Ergon upholstery	Office furniture manufacturing	7.95	0.814	90	133	908.2	26.4
30	Curler	Fibre drum manufacturing	8.13	1.429	71	20	1055.0	47.3
31	Hand Op 2	Fibre drum manufacturing	8.5	1.430	81	20	1000.0	21.9
32	Hand Op 1	Fibre drum manufacturing	8.5	1.670	82	20	1142.2	38.0
33	Transfer task	Laboratory	8.35	0.667	61	10	1288.0	28.9

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 equations $V_{\mathrm{p}x,i} = (\mathrm{p}x_{i+1} - \mathrm{p}x_{i-1})/2\Delta$, $V_{\mathrm{py},i} = (\mathrm{p}y_{i+1} - \mathrm{p}y_{\mathrm{i}-1})/2\Delta$ and $V_{xy,\mathrm{video}} = \sqrt{(V_x)^2 + (V_y)^2}$, where p$x$ is the pixel location on the x axis, py is the pixel location on the y axis and $V_{xy,\mathrm{video}}$ 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.

Speed was first calculated in units of pixels per second and then converted into physical units of millimetres. 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 (Greiner 1991) HB anthropometry survey database. The analyst identified the active hand in each video segment and measured the HB in units of pixels using MVTA software (Yen and Radwin 1995). HB was used because of its small coefficient of variation of 0.046 for males and 0.048 for females. Hand speed root mean square (RMS) was calculated using the equation

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

where exertion time $T = T_{E_2} - T_{E_1}$. This calculation is illustrated in Figure 1. The calibrated RMS speed (mm/s) is plotted against HAL in Figure 2.

In order to examine the effect of the variation of HB on the scaled RMS speed and the predicted HAL values, a Monte Carlo method was employed such that a HB 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 HB to the measured pixel HB was calculated and RMS speed was scaled to mm/s. A regression equation for HAL was first estimated, and another random set of HB sizes was selected for each of the 33 jobs

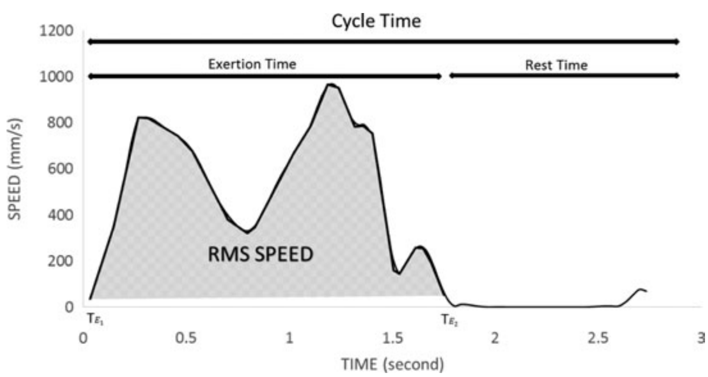

Figure 1. Representative plot of speed versus time. RMS speed is calculated only during time periods when motion/exertions are performed.

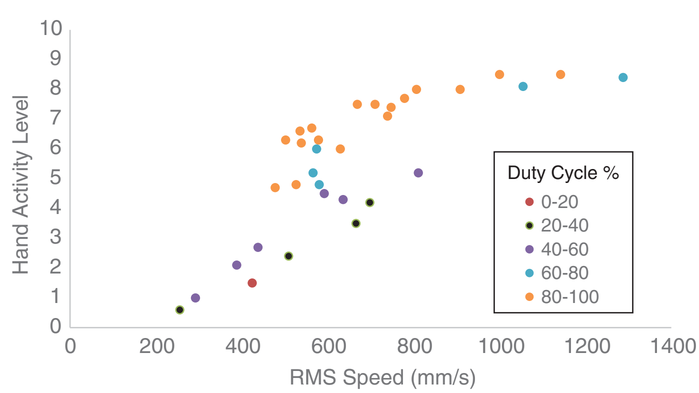

Figure 2. A plot of HAL versus measured RMS speed (S) estimated for the 33 jobs from Latko et al. (1997).

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.

2.1 Linear regression equation

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

$$\mathrm{HAL} = b_0 + b_1 S + b_2 D.$$

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

2.2 Logit-linear regression equation

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

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

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

2.3 Equation validation

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 was 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 analysed 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 rest period definitions were consistent with Latko et al. (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.

3. Results

3.1 Linear regression equation

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

$$\mathrm{HAL} = -1.16 + 0.0047\,S + 0.053\,D. \quad (2)$$

The upper boundary, lower boundary and means for these predictions are shown in Figure 3. 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 is shown in Figure 4.

Table 2. Summary of the linear regression coefficients from Monte Carlo simulation for varying HB ($N = 580$).

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	

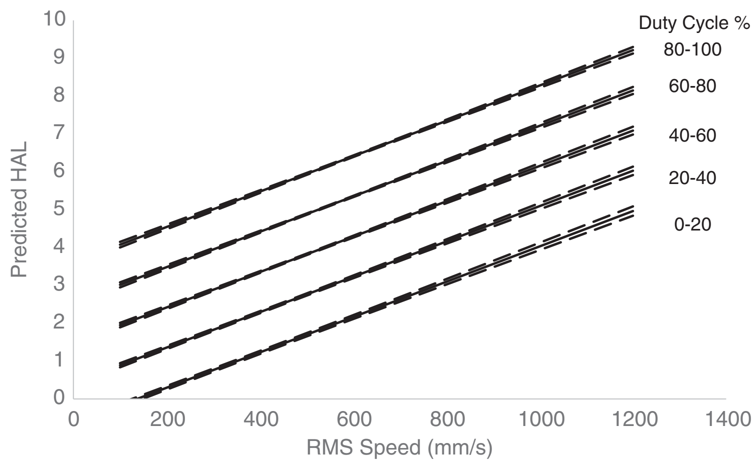

Figure 3. Plot of the linear equation for predicted HAL as a function of speed (S) and duty cycle (D). The solid line represents the average regression line and the dotted lines represent the 0.1 percentile and 99.9 percentile of predicted HALs resulting from the Monte Carlo method.

3.2 Logit-linear regression equation

The logit-linear regression equation is summarised in Table 3 and is plotted in Figure 5. 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 was 0.97 (Nagelkerke 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 6. The equation was

$$\mathrm{HAL} = 10\left[\frac{\mathrm{e}^{-15.87+0.02\,D+2.25\ln S}}{1+\mathrm{e}^{-15.87+0.02\,D+2.25\ln S}}\right]. \tag{3}$$

The residual range (Figure 6) was less than ± 0.5 HAL, which was considerably better than the linear regression equation.

3.3 Equation validation

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 ($p < 0.001$), $R^2 = 0.97$, and is plotted in Figure 7(a). The logit-linear equation-predicted HAL and the observed HAL values had a slope of 0.99 ($p < 0.001$), $R^2 = 0.99$, and is plotted in Figure 7(b). The analysis of variance for the F equation and the S logit-linear equation is provided in Table 4. The mean square error for the nonlinear regression equation for HAL based on F (Radwin et 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.

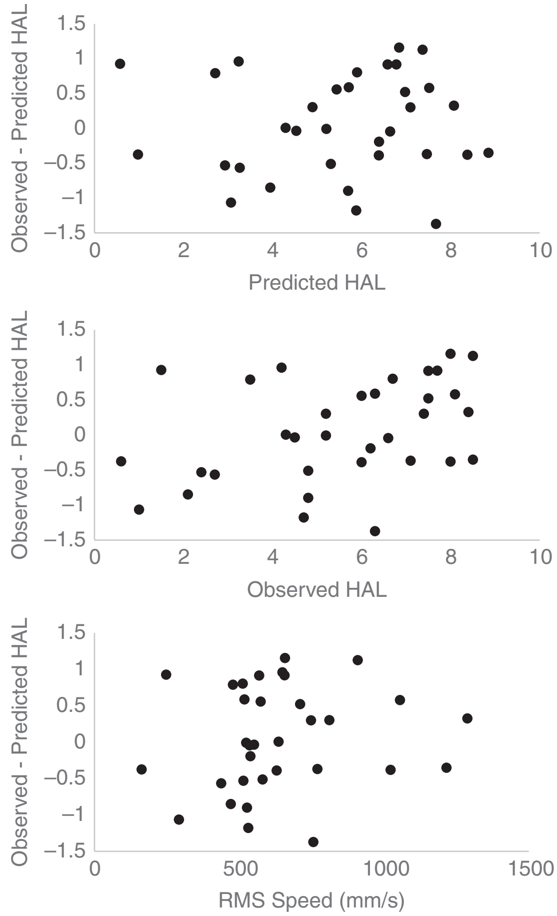

Figure 4. Linear equation residuals for observed–predicted HAL versus predicted HAL, observered HAL and RMS speed.

4. Discussion

In this study we analysed videos for the 33 jobs from Latko et al. (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 labelled slow motions and HALs of 8–10 are labelled 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 162–1288 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.

Table 3. Summary of the logit-linear regression coefficients from Monte Carlo simulation for varying HB ($N = 580$).

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	

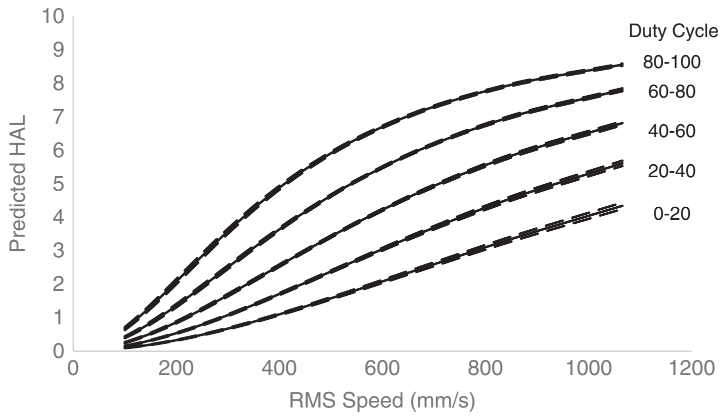

Figure 5. Plot of the logit-linear equation for predicted HAL as a function of speed (S) and duty cycle (D). The solid line represents the average regression line and the dotted lines represent the 0.1 percentile and 99.9 percentile of predicted HALs resulting from the Monte Carlo method.

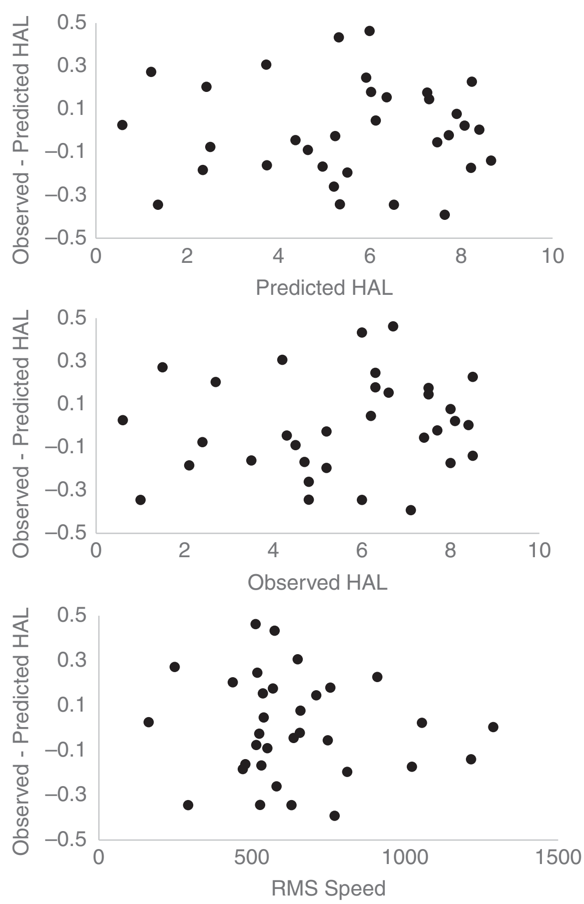

Figure 6. Logit-linear equation residuals for observed–predicted HAL versus predicted HAL, observered HAL and RMS speed.

We conclude from the Monte Carlo simulation that HB 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 normalised to HB. For example, a worker has 355.6 pixels/s measured hand speed and using average male HB (90.4 mm), the speed scaled to 726.57 mm/s, yielding HAL of 5.2.

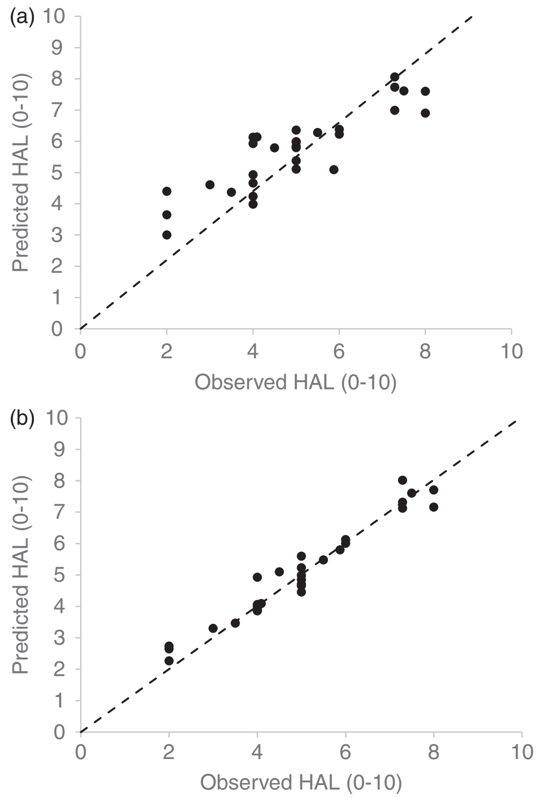

Figure 7. Predicted HAL plotted against observer-rated HAL (from Harris et al. 2011) for (a) the linear *S* equation (Equation (2)) and (b) the logit-linear *S* equation (Equation (3)).

Table 4. ANOVA for validation regression.

	df	SS	MS	*F*	Significance
Predicted HAL using F *equation (Equation (1)) versus observed HAL*					
Regression	1	784.47	784.48	611.49	< 0.001
Residual	29	37.20	1.28		
Total	30	821.68			
Predicted HAL using S *linear model (Equation (2)) versus observed HAL*					
Regression	1	798.25	798.25	988.23	< 0.001
Residual	29	23.43	0.81		
Total	30	821.68			
Predicted HAL using S *logit-linear equation (Equation (3)) versus observed HAL*					
Regression	1	817.04	817.039	5108.75	< 0.001
Residual	29	4.64	0.16		
Total	30	821.68			

If the worker had the maximum HB 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 HB 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 90th and 10th percentile HB yields HAL ranges in between 4.7 and 5.4 which gives a maximum difference of 0.5 HAL. Thus an average HB 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 HB.

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 than the equation based on *F* (Radwin et 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 et 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.

5. Conclusions

Based on these findings, the following conclusions are made:

(1) 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).
(2) A Monte Carlo method demonstrated that hand speed can be acceptably estimated, when a distance reference measure is unavailable, by using the HB measured from the video scaled to a population mean HB (90.4 mm for males and 79.5 mm for females).
(3) 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).
(4) Semi-automatic video analysis of HAL would benefit from the use of the *S* equation, as well as single frame analyses of industrial jobs.

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