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A comparison between analysis time and inter-analyst reliability using spectral analysis of kinematic data and posture classification

Thomas Y. Yen, Robert G. Radwin*

Department of Industrial Engineering, University of Wisconsin-Madison, 1513 University Avenue, Madison, WI 53705, USA

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Abstract

This study compares the time needed to analyze data and the inter-analyst variability using observational posture classification vs. spectral analysis of upper limb kinematic measurements made using an electrogoniometer for selected industrial jobs. Eight trained analysts studied four jobs using both methods. An incomplete fixed block experimental design was used, whereby each analyst used one method for each job. The four jobs included (1) punch press operation, (2) packaging, (3) parts hanging, and (4) construction vehicle operation. The posture classification analysis method involved visually classifying upper extremity joint angles into specific zones relative to the range of motion for every one-third second (10 frames) of videotape. Spectral analysis required the analysts to identify cycle break points. The electrogoniometer signals were synchronized with each cycle, and power spectra for each joint were computed. The average difference in RMS joint deviation among analysts was 0.9° (SD $= 0.61^\circ$) for spectral analysis and 7.1° (SD $= 2.53^\circ$) for posture classification. The average difference in mean joint angle was 0.8° (SD $= 0.59^\circ$) for spectral analysis and 11.4° (SD $= 1.58^\circ$) for posture classification. Repetition frequency differed an average of 0.05 Hz (SD = 0.054 Hz) for spectral analysis and 0.07 Hz (SD = 0.058 Hz) for posture classification. Posture classification took a factor of 6.3 more time than cycle break point assignment for spectral analysis. Even considering the additional time needed for sensor attachment for direct measurement, posture classification took an average factor of 1.29 more time than spectral analysis using electrogoniometer data. © 2001 Elsevier Science Ltd. All rights reserved.

Keywords: Spectral analysis; Posture classification; Analysis time

1. Introduction

Posture classification is a widely used method for quantifying physical stress in the workplace. The time and resources required to analyze jobs often makes detailed posture classification impractical for industrial applications and prohibitive for large-scale epidemiological studies. Posture classification is often used for quantifying postural stress and repetitive motion, since little more equipment than a video camera and recorder are required (Priehl, 1974; Karhu et al., 1977; Armstrong et al., 1979; Corlett et al., 1979; Silverstein et al., 1986, 1987; Keyserling, 1986; Keyserling et al., 1991; McAttamney and Corlett, 1993; Wells et al., 1997). However, these measurement methods are extremely limited in their ability to fully characterize physical stress exposure. They lack resolution, take a great deal of time, require highly trained observers, and are subject to analyst biases and experience. Consequently, many epidemiological studies have been limited to coarse measures (Winkel and Westgaard, 1992; Keyserling et al., 1991; Silverstein et al., 1986, 1987; Drury, 1987; Habes and Putz-Anderson, 1985; Armstrong et al., 1979; Corlett et al., 1979; Karhu et al., 1977; Priehl, 1974).

Ability to estimate upper arm posture was previously tested in a laboratory setting with a perpendicular sagittal plane view and good contrast (Ericson et al., 1991). Median errors of 5° for static postures, and 10–13° for dynamic postures were obtained. Although Genaidy et al. (1993) reported a much smaller mean error of 1.3° for upper arm posture estimates from a group of untrained subjects, observers tended to overestimate true angles ranging from 1° to 60°, and underestimate angles ranging from 61° to 180°. Static posture estimation of the wrist and elbow were the most difficult,

*Corresponding author. Tel.: +1-608-263-6596; fax: +1-608-262-8454.

E-mail address: radwin@engr.wisc.edu (R.G. Radwin).

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with the body orientation greatly influencing the accuracy (Baluyut et al., 1997). Posture estimates for industrial applications could have more error than in the laboratory since the ability to have a perpendicular view and a high contrast videotape of the job may be difficult to obtain in the field. Direct biomechanical measurements have better accuracy and precision, but require more complex measurement methods.

One of the main limitations of using biomechanical data such as joint angles measured using electrogoniometers for physical stress exposure assessment is the overhead associated with managing large quantities of data. Direct measurement of dynamic motions from multiple joints can produce data very rapidly. As a result, analysis of continuous posture and force has been only practical for limited observation time, such as 5 min segments of video that best represented the work (Moore et al., 1991; Marras and Schoenmarklin, 1993). An efficient data reduction method is therefore needed for handling the abundance of biomechanical data that inevitably is collected.

Spectral analysis has been found useful for characterizing repetitive motion, postural stress, and average joint angle in the laboratory using simulated industrial tasks in the lab (Radwin and Lin, 1993; Radwin et al., 1994) and for actual industrial tasks in the field (Yen and Radwin, 1997, 2000). Radwin and Lin (1993) demonstrated that spectral analysis can resolve differences in repetitiveness for specific aspects of repetitive manual tasks. The DC component of the spectrum is a metric of postural stress and indicates the average joint angle. The AC frequency components of the spectrum are related to the rate of repetitive movements. The magnitude of each spectral component indicates joint deviation for its corresponding repetition rate.

This study compares the required analysis time and the inter-analyst variability between the spectral analysis and posture classification methods. Trained analysts studied the same jobs using one of the two methods. Differences and similarities among analysts for the two quantification methods are compared.

2. Methods

2.1. Posture classification analysis

The observational posture classification method developed by Armstrong et al. (1982) was used because of its documented use (Habes and Putz-Anderson, 1985; Armstrong et al., 1986; Silverstein et al., 1986, 1987; Keyserling et al., 1991). Upper extremity postures were specified by their location about three axes of rotation for the shoulder, two axes for the elbow, and two axes for the wrist. Postures for each axis of rotation were assigned one of three to six values corresponding to the joint position (refer to Table 1).

The analyst estimated joint angles visually by observing every 10th video frame (30 frames/s) and indicating the appropriate angle for each joint. This produced a 3 samples/s time series and with a magnitude resolution for each joint shown in Table 1. A computer program was written to help implement the posture classification analysis using a computer-controlled VCR. The program displayed joint posture classifications for the shoulder, elbow, wrist, and hand. The desired joint angle ranges were selected by clicking the computer cursor on checkboxes associated with the joint angle (see Fig. 1). After all the joint postures were entered for the

Table 1
Posture classification joint angles

Articulation	Posture classification zones					
Shoulder flexion, extension	Flex (0°) (<40°)	45° (40–60°)	90° (60–120°)	135° (120–160°)	Neutral (180°) (160–200°)	Extend (225°) (>200°)
Shoulder adduction, abduction	Abduct (−90°) (<−90)	−45° (−90–−40°)	Neutral (0°) (−40–10°)	Adduct (45°) (10–60°)		
Elbow angle	Flex (135°) (>100°)	90° (100–70°)	45° (70–35°)	Extend (0°) (<35°)		
Forearm rotation	Prone (−70°) (<−15°)	Neutral (0°) (−15–45°)	Supine (90°) (>45°)			
Wrist deviation	Radial (−15°) (<−5°)	Neutral (0°) (−5–15°)	Ulnar (20°) (>15°)			
Wrist angle	Flex (−75°) (<−45°)	45° flex (−45°) (−45–−15°)	Neutral (0°) (−15–10°)	45° ext (45°) (10–45°)	Extend (75°) (>45°)	

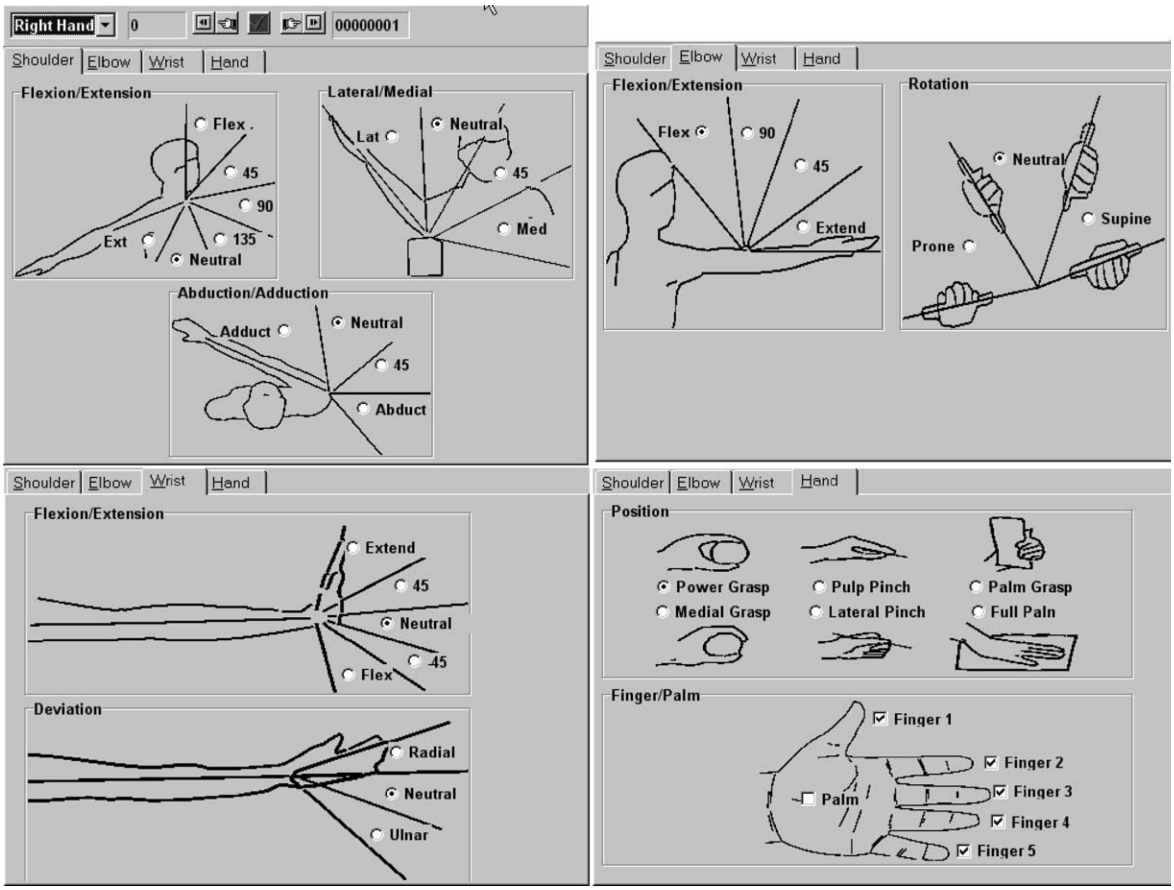

Fig. 1. Computer screen images of the computerized posture classification analysis.

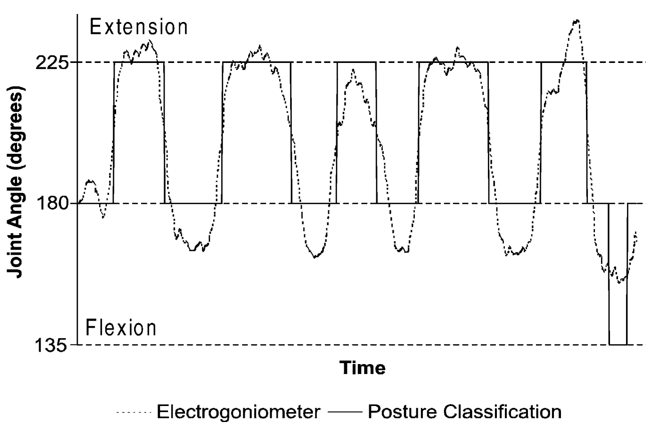

Fig. 2. Shoulder joint angles determined by analysts using posture classification and direct measurement from electrogoniometer.

current video frame, the VCR was automatically advanced 10 frames by the computer.

A representative record of posture angles obtained from posture classification as compared to the directly measured electrogoniometer signal is illustrated in Fig. 2 for shoulder flexion/extension. The average joint angle and RMS joint deviation for the observational analysis were computed from the resulting time series data. The posture classification time series data was partitioned into segments based on the cycle break points determined by the analyst. The mean joint angle was calculated by the arithmetic mean of the time series over each cycle. The RMS joint deviation was calculated from the joint posture classification time series over each cycle. The repetition rate for each joint was the average inverse of the time interval between specific motions.

2.2. Spectral analysis

An interactive computer-controlled video-based analysis system was developed for recording kinematic data associated with manual tasks and for extracting data corresponding with particular work elements (Radwin and Yen, 1993; Yen and Radwin, 1995). Upper extremity joint angles were measured using commercial electrogoniometers (Penny and Giles, Ltd. and Exos, Inc.). Analog signals from the electrogoniometers were sampled at 60 points/s, digitized, encoded, and recorded on the audio track of VHS tape along with the video image. Video cameras recorded workers from two camera viewpoints and were mixed for a split screen image (see Fig. 3). Joint motions included wrist flexion/extension, ulnar–radial deviation, forearm rotation, elbow flexion/extension, shoulder flexion/extension, and shoulder adduction/abduction. By individually calibrating each of the joint motions within the range of motion limits for each task using a manual goniometer, less than 5% error was obtained for the wrist and elbow joints and 10% for the shoulder (Yen and Radwin, 2000).

A computer-controlled VCR (see Fig. 4) enabled the analyst to review the tape while observing the work activities at any desired speed or arbitrary sequence (real-time, slow motion, fast motion, or frame-by-frame in either forward or reverse direction). The analyst assigned event markers for cycle break points by advancing the videotape to the video frame representing the break point and pressing a key on the keyboard or clicking the mouse. The assignment of the break points need not be performed in any specific sequence. When an event was selected, the time code address associated with the video image and data at that time was stored in a list as the start of the activity or task element, and also indicated the termination of the previous activity. The tape could be rewound or shuttled backwards to the point on the tape before the assignment, and a deletion or correction can be made. The biomechanical data corresponding to each task cycle were extracted by the computer from the videotape and processed using spectral analysis. The analyst was only responsible for defining the cycle break points, with the remainder of the analysis performed by the computer.

Power spectra were calculated for each cycle of sampled electrogoniometer data and the spectra were averaged over all cycles (Radwin et al., 1994). Three spectral parameters were determined. Repetition was determined from the frequency (Hz) where a spectral peak occurred. Joint angle deviation was the area under the spectrum, expressed in terms of RMS (deg), and the average joint angle of the spectrum 0 Hz DC component (deg).

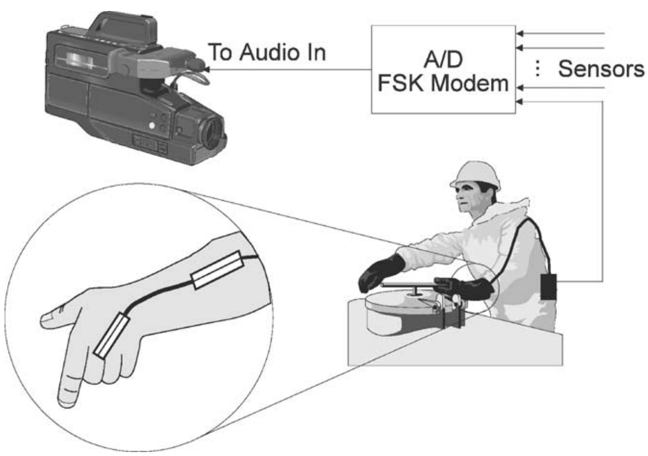

Fig. 3. Data acquisition system used in this study.

2.3. Experimental procedures

The four jobs selected consisted of (1) press operation, (2) product packaging, (3) small parts hanging, and (4) construction vehicle operation. A description of each job is summarized in Table 2. The jobs were selected because of workstation features or job requirements that emphasized repetitiveness or postural stress.

The eight subjects were graduate students in ergonomics, trained as analysts for this study. The subjects did not have any previous hands-on experience with either of the two analysis programs, but were all familiar with posture classification techniques. Group training was conducted to introduce the analysts to the equipment, software, analysis methods, and the four jobs to be analyzed. The training familiarized the analysts with the break point identification and posture classification

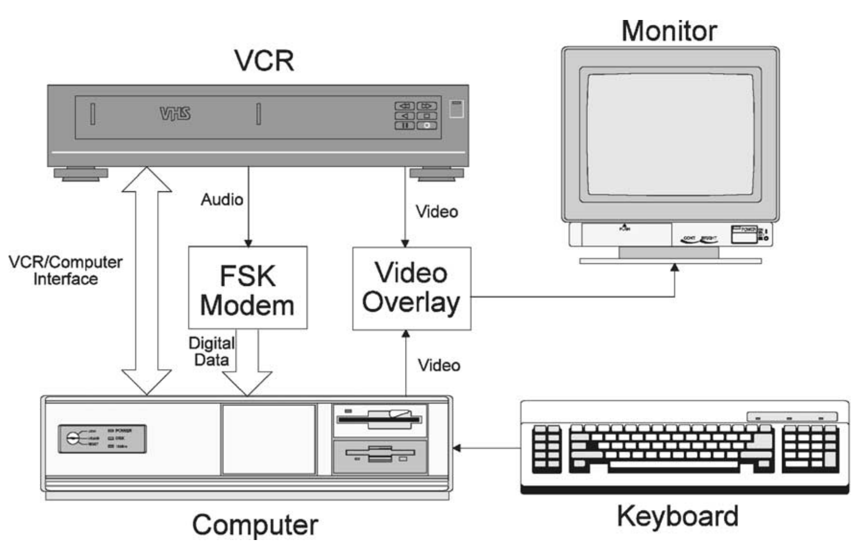

Fig. 4. Data extraction and analysis system used in this study.

Table 2
Description of analyzed jobs

Job name	Job description	No. of cycles	Elements per cycle
(1) Press operation	Pick up part in one hand and transfer it to a tool in the other hand. Transfer the part to a press fixture. Activate press by depressing buttons with both hands	15	5
(2) Parts hanging	Pick up parts from bin and hang on hooks located at two different heights traveling on a conveyor system	10	4
(3) Product packaging	Pick up product off conveyor and stack in a box. The box was angled so the open end faces the worker	15	3
(4) Construction vehicle operation	Operate a wheel loader vehicle for a load/unload task	3	3

conventions for each job, ensuring that all analysts were using the same break point and posture definition. The group training lasted 3 h. In addition, each analyst also received a minimum of 4 h of individual training and practice for both methods using a training tape. The training tape contained a video of four similar, but distinctly different jobs than the ones used for the actual analysis. To reduce learning effects, analysts studied each job until they reported they were comfortable identifying postures and break points. The subjects were instructed to perform the analyses as quickly as possible, emphasizing accuracy and consistency.

The experiment was an incomplete block design. Each analyst studied all four jobs but used a single analysis method for each job. The method to be used was counterbalanced across jobs. Four analysts using the same method analyzed each job. The time elapsed for completing the analysis was recorded.

Comparisons between subjects for corresponding analysis methods were performed. Differences among the analysts for each physical stress parameter and analysis method were compared. Analysis of variance was performed to determine significant differences in time between analysts, jobs, and methods. Analysis of variance was also performed on the mean difference between the average joint angle, RMS joint angle, and repetition frequency for each method.

3. Results

The overall data collection and analysis time, including camera setup, sensor setup and calibration, is shown in Fig. 5. A camera setup time of 15 min represented the typical time allotted to set up two cameras. The sensor setup time for mounting four electrogoniometers (two biaxial for wrist flexion/extension and ulnar/radial deviation, and shoulder flexion/extension and shoulder abduction/adduction; one single axis for elbow flexion, and one torsional for forearm rotation) onto the joints of the subject using double-sided adhesive and surgical

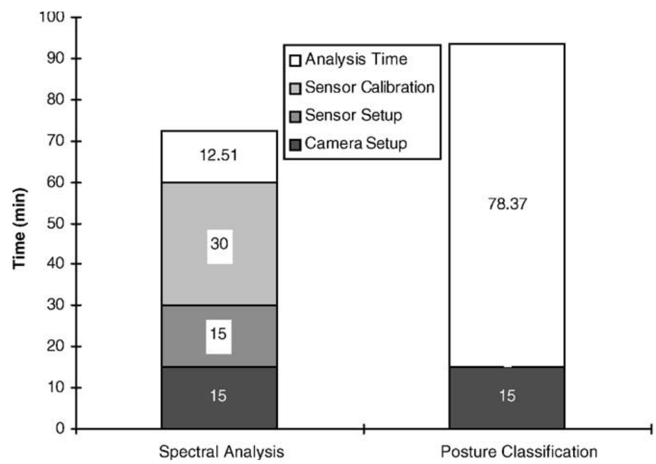

Fig. 5. Overall data collection and analysis time comparison between spectral analysis and posture classification.

tape was 15 min. The sensor calibration for six joint motions was completed in 30 min.

The time elapsed for each analysis method is summarized in Table 3. The analysis times were significantly different among the eight analysts ($F(7,20) = 4.31$, $p \leqslant 0.05$), jobs ($F(3,20) = 6.37$, $p \leqslant 0.05$), and analysis method ($F(1,20) = 150.65$, $p \leqslant 0.05$). The spectral analysis method required 16% of the time that was needed for posture classification. The mean analysis time was 12.52 min (SD = 4.20) per minute of tape for spectral analysis and 78.69 min (SD = 21.58) per minute of tape for posture classification. The mean difference in cycle break points between analysts ($F(1,15) = 2.12$, $p > 0.05$) was 0.136 s (SD = 0.086 s). The mean difference between posture assignments classification ($F(1,15) = 5.70$, $p \leqslant 0.05$) was 14.24° (SD = 3.64°).

The results for average joint angle, RMS joint angle, and repetition frequency are shown in Tables 4–6, respectively. The average joint angle and standard deviation among the analysts for each job estimated the variation among the analysts. The average joint angle difference among analysts was 2.9° (SD = 2.52°)

Table 3
The analysis time (min) required for each analysis method

Job	Analyst								Mean (SD)
	1	2	3	4	5	6	7	8	
Posture classification method									
1		129.75	104.75		123.75			129.75	122.00 (11.84)
2		103.25		106.25	111.25		195.25		129.00 (44.29)
3	123.25		118.25			68.25		148.25	114.50 (33.51)
4	51.00			40.0		29.00	124.00		61.00 (42.95)
Mean (SD)									106.63 (30.99)
Spectral analysis method									
1	9.00			5.00		25.00	40.00		19.75 (16.03)
2	10.00		11.00			20.00		52.00	23.25 (19.69)
3		17.00		3.00	16.00		29.00		16.25 (10.63)
4		15.00	4.00		8.00			9.00	9.00 (4.54)
Mean (SD)									17.06 (6.09)

Table 4
Average joint angle (deg)

Job	Analyst								Mean	SD
	1	2	3	4	5	6	7	8		
Posture classification method										
1		35.4	50.5		40.8			38.0	41.2	6.6
2		46.7		41.0	34.5		45.0		41.8	5.4
3	44.9		35.4			33.3		40.6	38.6	5.2
4	47.1			46.7		41.3	33.5		42.2	6.3
Spectral analysis method										
1	−7.9			−8.0		−7.9	−8.0		−8.0	0.0
2	41.9		40.6			41.2		41.5	41.3	0.6
3		21.4		19.7	19.8		21.6		20.6	1.0
4		39.4	39.4		40.6			39.8	39.8	0.6

Table 5
Average RMS joint deviation (deg)

Job	Analyst								Mean	SD
	1	2	3	4	5	6	7	8		
Posture classification method										
1		21.9	25.3		29.5			26.3	25.8	2.7
2		11.3		19.9	28.1		13.7		18.2	6.5
3	22.8		21.1			21.1		20.7	21.4	0.8
4	3.3			2.2		2.9	6.5		3.7	1.6
Spectral analysis method										
1	9.4			9.5		9.4	9.5		9.4	0.1
2	14.0		13.7			13.0		14.1	13.7	0.4
3		9.4		10.5	11.0		9.5		10.1	0.7
4		4.1	4.1		5.4			7.4	5.3	1.3

for posture classification and 0.6° ($SD = 0.55^\circ$) for spectral analysis. The average RMS joint angle difference among analysts was 5.9° ($SD = 0.67^\circ$) for posture classification and 0.6° ($SD = 0.41^\circ$) for spectral analysis. The average repetition frequency difference among analysts was 0.069 Hz ($SD = 0.055$ Hz) for posture classification and 0.039 Hz ($SD = 0.48$ Hz) for spectral analysis. Statistically significant differences were

Table 6
Average repetition frequency (Hz)

Job	Analyst								Mean	SD
	1	2	3	4	5	6	7	8		
Time study method										
1	0.644			0.654		0.784		0.440	0.631	0.142
2	0.492		0.492			0.403	0.451		0.460	0.042
3		0.729		0.586	0.549			0.620	0.622	0.078
4		0.079	0.079		0.067		0.103		0.082	0.015
Spectral analysis method										
1	0.508			0.508		0.527	0.508		0.513	0.010
2	0.375		0.387			0.393		0.375	0.382	0.009
3		0.316		0.375	0.316		0.340		0.337	0.028
4		0.070	0.070		0.141			0.305	0.147	0.111

observed between the analysis method used for the average joint angle ($F(1,7) = 183.91$, $p \leqslant 0.05$). No significant difference was observed between the analysis methods for the RMS joint angle ($F(1,7) = 30.15$, $p > 0.05$) or repetition frequency ($F(1,7) = 0.68$, $p > 0.05$).

The average difference among analysts for average joint angle was 0.8° (SD = 0.59°) for spectral analysis and 11.4° (SD = 1.58°) for posture classification. The average difference for RMS joint angle was 0.9° (SD = 0.61°) for spectral analysis and 7.1° (SD = 2.53°) for posture classification. Repetition frequency differed an average of 0.05 Hz (SD = 0.054 Hz) for spectral analysis and 0.07 Hz (SD = 0.055 Hz) for posture classification. Statistically significant differences were observed between analysis methods for average joint angle ($F(1,7) = 155.44$, $p \leqslant 0.05$), with posture classification having more than an average of 10° greater angles than spectral analysis. Statistically significant differences were observed between analysis method for RMS joint angle ($F(1,7) = 22.66$, $p \leqslant 0.05$), with posture classification having more than an average of 9° greater joint deviation error than spectral analysis. Repetition frequency was not statistically significant for analysis method ($F(1,7) = 0.15$, $p > 0.05$).

4. Discussion

Overall, analysis time for posture classification was a factor of 6.3 times more than for spectral analysis of directly measured data. The utility of direct measurement has been questioned because of the extra time required to set up and calibrate the sensors (Kilbom, 1994). The current study indicated that the extra setup time was far surpassed by the time necessary for performing posture classification analysis. The overall data collection and analysis time for spectral analysis was 72.51 min while posture classification was 93.37 min.

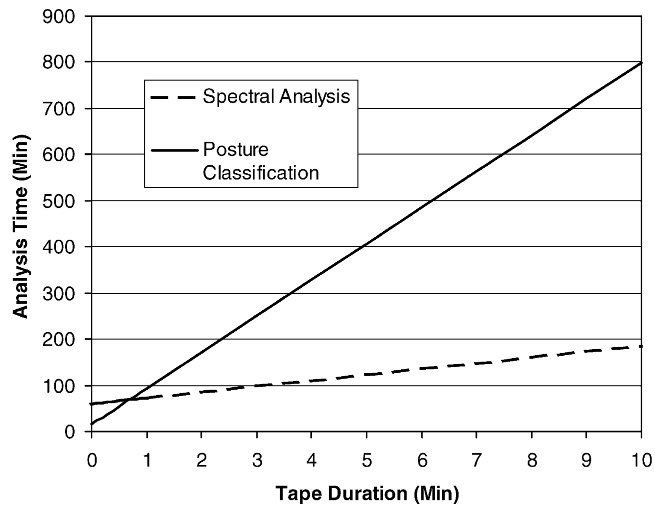

Fig. 6. Data collection and analysis time comparison between spectral analysis and posture classification for a given videotape duration.

Spectral analysis of direct measurement data required 23% less time than posture classification. Greater analysis time improvements are anticipated when longer samples of work activity are analyzed. Assuming a fixed setup time for both analysis methods, and the analysis times for posture classification was 78.69 min per minute of tape, and spectral analysis was 12.52 min per minute of tape. The analysis time needed for the two methods for a given duration is compared in Fig. 6. When less than 40 s of tape is analyzed, posture classification takes less time. When more than 40 s of tape are studied, spectral analysis of direct measurement data would be more time efficient. The breakeven time of 40 s is for 120 posture analysis observations (3 observations per second).

Keyserling (1986) introduced a methodology using videotape and a computer for identifying nine levels of trunk posture and three levels of shoulder posture. The analysis time for 1 min of tape for a non-novice (more than 20 h of experience) was 20 min, and for a novice (less than 5 h of experience) was 45 min. Using non-novice analysts (more than 7 h of experience), spectral analysis required almost one-third less time than what Keyserling (1986) observed with non-novice analysts and provide results for six joints instead of three (trunk and both shoulders). Posture classification analysis time took more than three times that of the Keyserling method using non-novice analysts; however, more posture angle information and time resolutions were included. In the current study, posture was sampled every one-third second for six joints using 3–15 cycles, where Keyserling used only two or three representative cycles.

A minimum of 7 h of training was provided. This included 3 h of group training; so analysts all learned the same technique, criteria for angle estimation, and the use of the computer program. A minimum of 4 h of individual training was needed to become efficient with the computer program for both analysis methods and the four types of jobs to be analyzed. The analysts trained using similar types of jobs to the ones used in the actual study. The analysts reported that they felt this level of training was sufficient. We anticipate that additional training would not have a large influence. Environmental factors such as lighting and obstructions greatly influenced the quality of observations.

The variation in results among the analysts and analysis methods were consistent. Posture classification had a factor of 10.7 times more variation for average joint angle and a factor of 4.7 times more variation for RMS joint deviation than for spectral analysis. Posture classification had a factor of 1.87 times more variation among analysts than spectral analysis for repetition frequency. Although the differences for RMS joint deviation and repetition frequency measurements were not statistically significant, there was considerable variability (see Tables 5 and 6).

The best posture classification precision was $\pm 22.5^\circ$ (see Table 1 and Fig. 2). Consequently much of the joint angle magnitude information was lost when joint angles were coded into a single angle value, particularly when joint motions were small (see Fig. 2). Posture classification only indicated joint deviations when the joint angle exceeded the classification angle partitions. Joint motions smaller than the angle resolution were incorrectly coded as static. In addition, the posture classification contains error from poor visual contrast, parallax, and field of view. Baluyut et al. (1997) revealed that visual posture estimation from a TV screen can introduce substantial error in the estimation. Greater estimation errors occurred for the wrist and elbow joints, and were also influenced by the overall body orientation.

Previous studies (Keyserling, 1986; Ericson et al., 1991; Genaidy et al., 1993; Ortiz et al., 1997; Leskinen et al., 1986) comparing observational data with measured data have found good agreement between analysts and the objective measures. Using direct observation, analysts obtained errors of 10–13° for dynamic motions (Ericson et al., 1991) and a mean error of 1.3° for static postures (Genaidy et al., 1993). Comparisons between the analysts and objective measures were based on whether the observers selected the appropriate joint angle partition based on the actual joint angle, instead of comparing the error between the analysts and an objective measure. Even with observational errors as great as 13°, it was within the posture classification partition resolution, which masks the inaccuracy of the observers by producing good agreement between analysts. In the current study, the joint angles for posture classification were based on the analyst's judgment compared to the joint angle determined from direct measurement. The current study observed a 14° difference in average joint angle between posture classification and spectral analysis. This result was in agreement with the findings of Ericson et al. (1991) even when considering errors introduced by making posture judgments from a TV monitor screen.

Eight analysts participated in this study, but due to the incomplete block design, the results are limited to four analyst sets. Other studies validating inter-analyst reliability of observational posture classification however, only tested two observers (Keyserling, 1986; Ortiz et al., 1997; Leskinen et al., 1986).

Tasks containing complex motions or many motions per cycle tend to increase the analysis time and influence posture classification estimations. The jobs studied were selected in order to provide a range of cycle times (number of cycles), number of task elements, and repetitiveness. Time estimates in Figs. 5 and 6 are admittedly influenced by the particular jobs studied, however these jobs are common repetitive industrial tasks, often the topic of this type of analysis.

The objective of the current study was to determine if the analysis time for spectral analysis was significantly faster than posture classification, and to determine how analyst variations can influence the analysis outcome. Statistically significant differences were observed with this experimental design. The job $\times$ analyst interaction was not obtainable using an incomplete block experimental design, but this interaction was not considered important for these purposes.

5. Conclusions

Spectral analysis of directly measured posture data using electrogoniometers can be an effective method of data collection and analysis, particularly for long observation times. Spectral analysis time was 16% of the time for posture classification, and overall data collection and analysis time was 23% of posture classification. Spectral analysis was less influenced by analyst variations than posture classification, with inter-analyst differences of 1°, which was an order of magnitude better than for posture classification.

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