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Quantitative assessment of hand motor function in cervical spinal disorder patients using target tracking tests

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Abstract—Cervical spondylotic myelopathy (CSM) is a chronic spinal disorder in the neck region. Its prevalence is growing rapidly in developed nations, creating a need for an objective assessment tool. This article introduces a system for quantifying hand motor function using a handgrip device and target tracking test. In those with CSM, hand motor impairment often interferes with essential daily activities. The analytic method applied machine learning techniques to investigate the efficacy of the system in (1) detecting the presence of impairments in hand motor function, (2) estimating the perceived motor deficits of patients with CSM using the Oswestry Disability Index (ODI), and (3) detecting changes in physical condition after surgery, all of which were performed while ensuring test-retest reliability. The results based on a pilot data set collected from 30 patients with CSM and 30 nondisabled control subjects produced a *c*-statistic of 0.89 for the detection of impairments, Pearson r of 0.76 with $p < 0.001$ for the estimation of ODI, and a *c*-statistic of 0.82 for responsiveness. These results validate the use of the presented system as a means to provide objective and accurate assessment of hand motor function impairment and surgical outcomes.

Key words: cervical spondylotic myelopathy, classifier, hand impairment, hand movement, machine learning, motor deficit, patient monitoring, quantification, spinal cord disorder, tracking test.

INTRODUCTION

Cervical spondylotic myelopathy (CSM) is a degenerative spinal disorder in the cervical (i.e., neck) region. It is the most common spinal cord dysfunction in adults over 50 yr of age in North America [1–2]. Chronic disc degeneration, inflammatory diseases, or other soft tissue abnormalities caused by CSM often result in significant

Abbreviations: ADL = activities of daily living, CIDP = chronic inflammatory demyelinating polyneuropathy, CSM = cervical spondylotic myelopathy, ICC = intraclass correlation coefficient, JOA = Japanese Orthopedic Association (scale), LDA = linear discriminant analysis, LOSOCV = leave-one-subject-out cross-validation, MAD = mean absolute difference, MAE = mean absolute error, mJOA = Modified Japanese Orthopedic Association (scale), MLR = multivariate linear regression, MVC = maximum voluntary contraction, NDI = Neck Disability Index, ODI = Oswestry Disability Index, QDA = quadratic discriminant analysis, ROC = receiver operating characteristic, SVM = support vector machine, SVR = support vector regression, TNR = true negative rate, TPR = true positive rate, UCLA = University of California Los Angeles.

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pressure on the spinal cord or nerve roots [1]. A major complaint of patients with CSM is the impairment of hand motor function [3], including symptoms such as loss of dexterity, numbness, stiffness, weakness, fatigue, and tremor. Specifically, previous studies in patients with CSM observed force overshoot during the initiation phase of gripping followed by an immediate correction response [4–5], which may significantly restrict fine hand motor control. This overshooting response results from exaggerated command signals adopted to compensate for biomechanical changes due to chronic cervical spinal cord injury, and it was further shown that cervical decompression surgery attenuates these overshooting responses [4]. These symptoms may develop into severe weakness or complete paralysis of hand movements [6]. Thus, frequent monitoring of physical conditions in patients with CSM is essential for assessing the impairment level, evaluating the results of medical treatment, and preventing possible onset of impairments.

Unfortunately, frequent radiographical testing (e.g., X-ray or magnetic resonance imaging) is extremely costly. Consequently, current methods for clinically assessing the progress or level of impairment rely on patient-reported outcomes such as the Oswestry Disability Index (ODI) [7] or Japanese Orthopedic Association (JOA) [8] measurements. However, these methods suffer from variability among responders and, most importantly, are known to carry response shift. Response shift refers to changes in an individual's internal standard of perceived health status, which often occurs after treatment such as a surgical intervention [9]. This reduces the reliability of using these methods for longitudinal tracking of patient progress [10–11].

Consequently, a simple, inexpensive, objective, and reliable assessment method for quantifying the physical condition of patients with CSM is needed [12]. Handgrip motor function has received attention as an area of focus for such an assessment method [13] since functional impairment of the hand closely relates to the quality of life of spinal disorder patients and to their ability to perform activities of daily living (ADL), such as eating, writing, or picking up small objects [12]. For instance, Sisto and Dyson-Hudson investigated various methods for using handgrip strength to determine mobility and self-care ability [12]. However, their work only considered the patients' abilities to exert a certain level of grip force rather than their abilities to control their fine hand movement [12], which has a greater correlation with ADL [14–16].

A target tracking test using handgrip force investigates patients' abilities to control their fine hand movement. Its clinical effectiveness has been well studied in other conditions, such as stroke [17–19], Parkinson disease [18,20], brain injury [14,21], and chronic inflammatory demyelinating polyneuropathy (CIDP) [19]. The target tracking test visualizes a predefined waveform that a subject must track by adjusting handgrip force in order to minimize the error between the waveform and the subject's response. Kurillo et al. showed that the tracking error was significantly larger in patients with neuromuscular diseases (e.g., stroke) than control subjects [18]. Lee et al. showed that patients' responses from the target tracking test contained motor characteristics that were specific to conditions such as stroke and CIDP [19]. Getachew et al. investigated the use of target tracking to quantify the level of hand impairment in patients with chronic spinal cord disorder, but their method employed a rather simple, single-dimensional metric (i.e., tracking error), which had considerable limitations in examining various aspects of hand impairments and their correlations to comprehensive quantification of motor deficits [22].

The goal of this work is to thoroughly investigate performance characteristics of the target tracking test in quantifying hand motor deficits in patients with CSM using machine learning techniques. Unlike previous works that used a simple and comprehensive metric, the method used in this work incorporates machine learning algorithms that mathematically combine multiple metrics (features) that are designed to represent known symptoms of CSM. We hypothesized that the quantification enabled by incorporating the target tracking test and machine learning techniques has the potential to serve as an effective screening and monitoring tool for hand motor function in patients with CSM. This work specifically aimed to investigate a number of important criteria for validating the medical efficacy of the target tracking test [23], including (1) detecting the presence of hand motor impairment and quantifying its severity [24], (2) estimating perceived motor deficits in performing daily activities using the ODI [7,25–26], and (3) detecting changes in physical conditions of patients after receiving surgical intervention (i.e., responsiveness [27–28]), all while ensuring the test-retest reliability of the quantification.

METHODS

Participants

A total of 30 patients with CSM (18 males), mean age 59.5 ± 16.0 yr, were recruited from the University of California Los Angeles (UCLA) Spine Center, excluding younger patients (<45 yr) and those with comorbidities affecting their hand motor function. All patients' evidence of CSM (e.g., location or level of the cervical spinal injury) was verified using conventional X-ray imaging. The average duration of overall back pain (both cervical and lumbar) of the participating patients was 49.9 mo, and the average duration of arm pain was 9.61 mo (until the date they received the surgical intervention). Radiculopathy (i.e., pinched nerve root) was found in 72.4 percent of the patients, while 68.9 percent had severe neck pain. All patients received spinal cord decompression to alleviate pressure on their impacted nerve roots, improving associated pain and motor function. The surgical intervention was performed by a single neurosurgeon, Daniel C. Lu (one of the coauthors of this article). Of the 30 patients, 17 returned to the clinic for follow-up within 3 mo of surgery. A total of 30 age-matched control subjects (14 male), mean age 57.5 ± 9.2 yr, were recruited from the general population.

Examination Protocol

This work used a handgrip device that has been described previously (**Figure 1**) [5]. The major components of the handgrip device include the springs, the handle, and the displacement sensor embedded in the body. The handle of the device was connected to the main frame by three springs, which provided physical resistance for grasping performance. The length of the handle could be customized using the adjustable pins to accommodate subjects with varying hand sizes. The springs could also be replaced to accommodate participants with varying grip strengths. This study used five springs with different tension forces: 0.38 lbs/in., 0.88 lbs/in., 1.94 lbs/in., 5.10 lbs/in., and 10.7 lbs/in. The displacement sensor was embedded in the bottom of the frame, and it captured the absolute position of the handle at a sampling rate of 32 Hz.

Participants started the test by measuring their maximum voluntary contraction (MVC), which represented the maximum grip force that participants could voluntarily exert. The measured MVC was used to normalize the maximum amplitude of the target waveform such that participants' fine motor function (rather than their absolute grip strength) could be investigated. The unit of the waveform amplitude was percent MVC. The waveform within the screen moved to the left while the horizontal

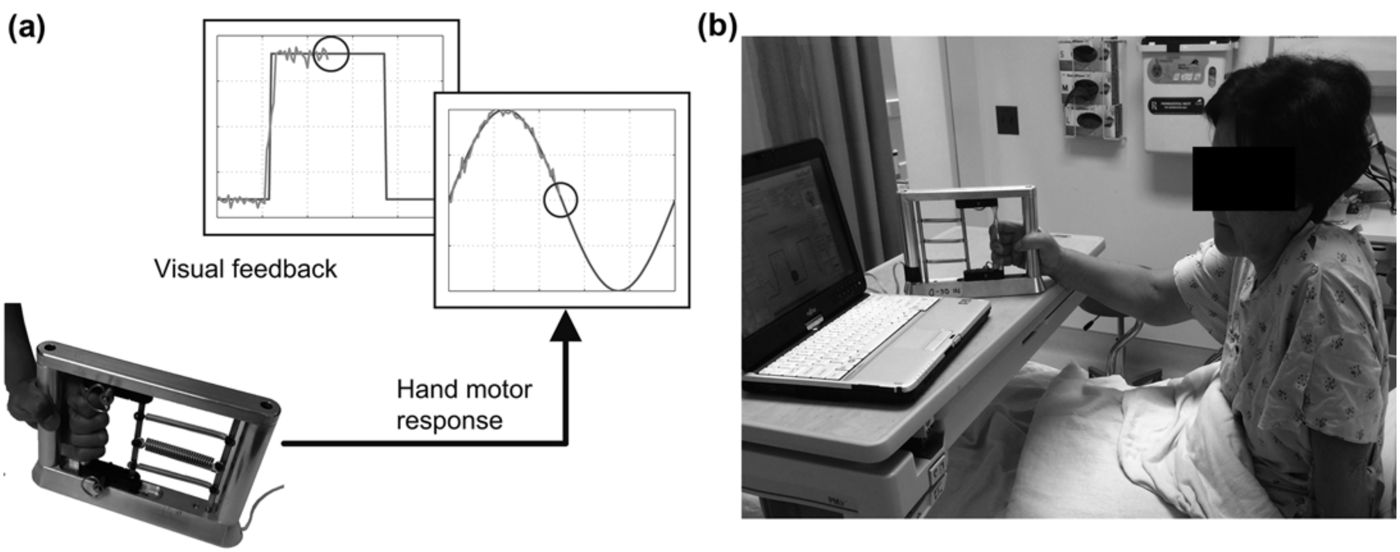

Figure 1.
(a) Handgrip device and the two tracking waveforms used in this study (left: step; right: sine). **(b)** Patient with cervical spondylotic myelopathy performing the test before her surgical operation.

position of the circle was fixed in the middle of the *x*-axis as shown in **Figure 1(a)**. The vertical position of the circle changed according to the grip force generated by the participants. The screen also displayed a trace history of the patient's response for visual feedback. The length of the test was 45 s.

Participants were tested using two different targets: sine and step waveforms. The sine waveform had a period of 6.17 s (0.16 Hz), which resulted in approximately seven sine cycles per test. The amplitude of the waveform changed from 0 to 100 percent of the subject's MVC, as illustrated in **Figure 2**. The sine waveform investigated participants' ability to predict and control the muscle movements required for grasping performance to be repeated at a constant rate [29]. The step waveform had a period of 3 s (0.33 Hz), with 50 percent duty cycle, which resulted in 15 cycles per test (**Figure 2**). The higher amplitude was equal to 80 percent MVC, and the lower amplitude was equal to 20 percent MVC. The step waveform investigated predictive tracking and the ability to produce handgrip force at a constant velocity [29]. Participants repeated each waveform three times per clinical visit, generating a total of six test results. The UCLA Institutional Review Board approved the examination procedure, and all participants provided consent after an explanation of the study protocol and the associated risks.

Patient-Reported Functional Outcomes

Patients with CSM reported their perceived level of motor impairment in performing ADL using the ODI [7] and the modified JOA (mJOA) at their preoperative and postoperative visits. ODI is one of the well-known measures of perceived motor function and quality of life for patients with spinal injuries [7,30]. It contains 10 multiple-choice items assessing the degree of interference from pain in performing various daily activities such as personal care, lifting, walking, sitting, standing, sleeping, sex life, social life, and traveling. The accumulated score ranges from 0 (no dysfunction) to 50 (completely disabled). In this work, the accumulated score was linearly scaled in reverse from 0 (completely disabled) to 1 (no dysfunction) to comply with the general systems performance theory that all dimensions of human performance should be in a form for which a higher numerical value represented superior performance. The mJOA is another well-known measure of motor deficits in patients with CSM [31]. This survey contains four multiple-choice items relating to upper-limb and hand motor function. The accumulated score of the mJOA ranges from 0 (completely disabled) to 18 (no dysfunction), which was again linearly scaled to 0 to 1.

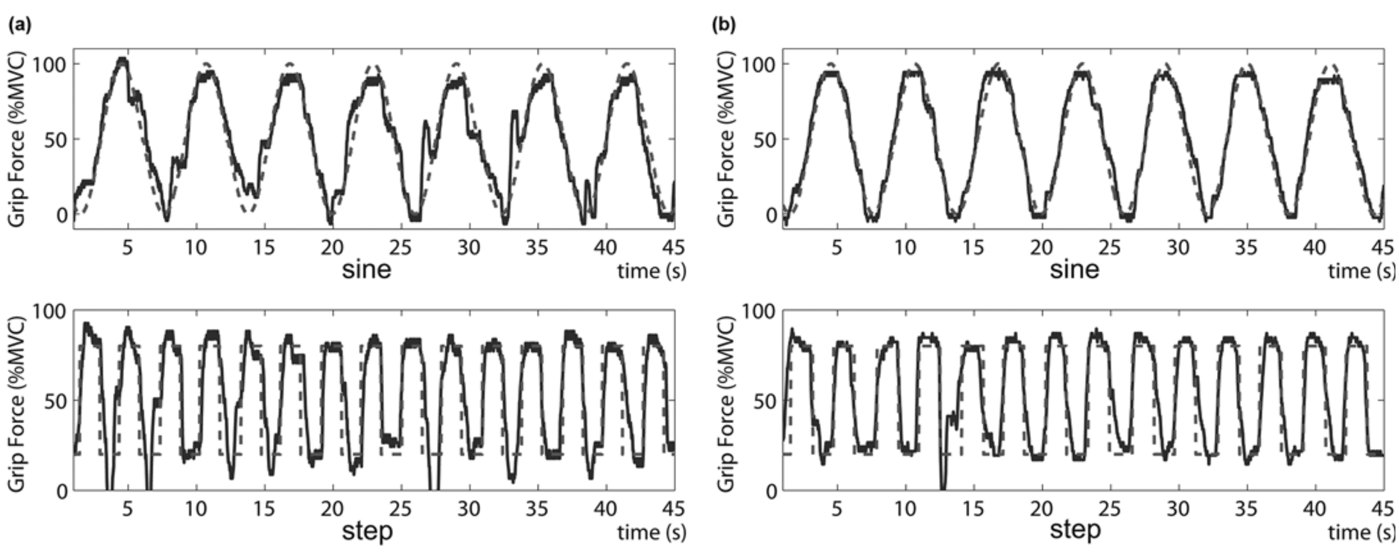

Figure 2.
Sample test results collected from **(a)** patients with cervical spondylotic myelopathy before surgery and **(b)** age-matched control subjects. MVC = maximum voluntary contraction.

Other Clinical Variables

Ten clinical variables that may have close correlation to hand motor impairment were collected. These variables included age, sex, overall back pain duration (how long had the current episode of back pain, both in cervical and lumbar areas, been present?), arm pain duration (how long had the current episode of arm pain been present?), presence of severe neck pain, presence of radiculopathy, herniated disks (i.e., C1 to C7), smoking or nonsmoking, packs of cigarettes smoked per year, and alcohol consumption (drinks per week). For nondisabled control subjects, age and sex information were collected.

Data Analysis

Figure 3 shows a schematic representation of the data analytics that were used to address the aforementioned objectives in a test-retest reliability manner. Impairment was detected by investigating the ability to differentiate the handgrip data collected from 30 preoperative patients with CSM (with impairments) from the data collected from 30 age-matched control subjects (without impairments). The estimation of the perceived motor deficits investigated the ability to estimate the ODI scores using handgrip data based on the data collected from 30 preoperative and 17 postoperative patients (i.e., a total of 47 data points from 30 patients). Finally, responsiveness investigated the ability to differentiate the patients whose perceived motor functions improved after the surgical intervention from those who did not improve. These objectives were addressed using the same data analytic platform, except that detection of impairments employed a binary classifier, estimating the perceived motor deficits employed a regressor, and responsiveness employed a binary classifier. For all objectives, employing a preprocessing step that eliminated those features that were unreliable ensured the test-retest reliability. All the components of the data analytics summarized in **Figure 3** are discussed in detail in the following subsections. Note that this work employed a leave-one-subject-out cross-validation (LOSOCV) to provide a fair evaluation of the quantification results; the data belonging to a subject was left out as a testing set, which was evaluated based on the classification/regression model constructed using the training data set belonging to the rest of the subjects. This approach avoids problems of overfitting and provides fair estimations of the expected diagnostic and estimation accuracy for the binary classifier and the regressor, respectively [32].

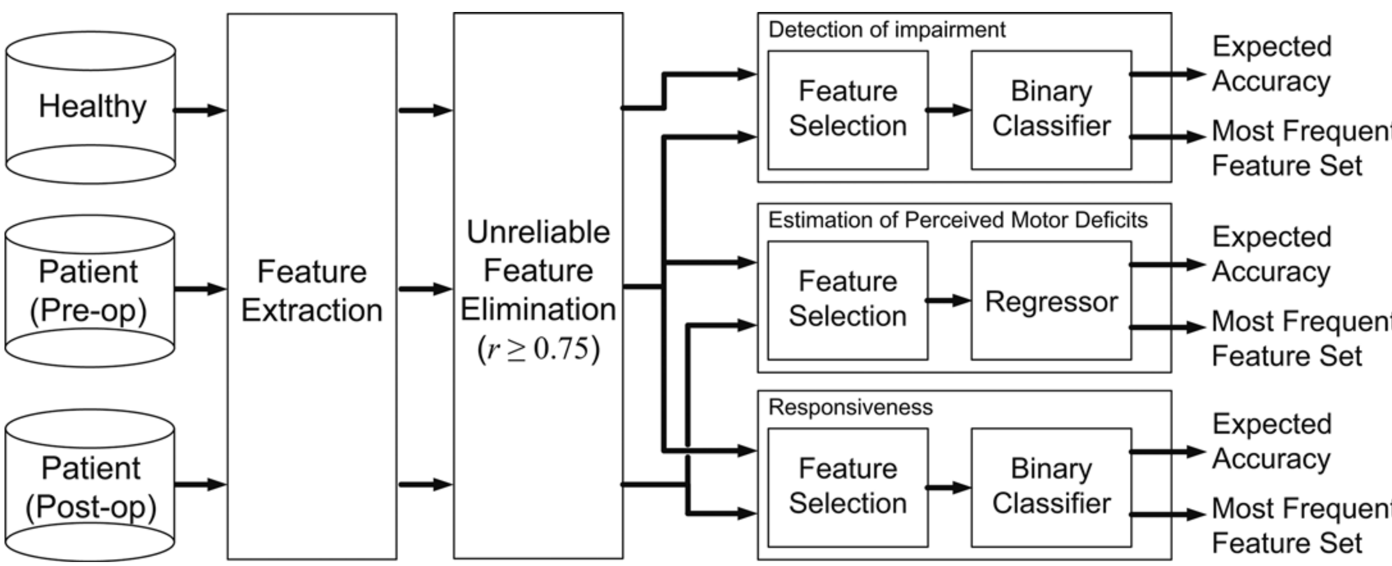

Figure 3.
Schematic representation of the data analyses that were used to address the aforementioned objectives: (1) ensuring the test-retest reliable of the quantification, (2) detecting the presence of hand motor impairment and quantifying the severity, (3) estimating perceived motor deficits in performing activities of daily living, and (4) responsiveness. Pre-op = preoperative, Post-op = postoperative.

Hand Motor Features

Sine waveform. The following features were extracted from the sine waveform: Mean absolute error (MAE) (MAE-SINE) computed the average error between the target sine waveform and the patient's response over the length of the signals: $\sum k \mid wt\ [k] - wr\ [k] \mid$, where wt and wr represented the target waveform and the patient's response, respectively. The level of the overshooting response during the initiation phase of gripping was uniquely observed in patients with CSM [4–5]. We further extended this finding by also considering the overshooting response during the release phase, as illustrated in **Figure 4**. The overshooting response from initiating gripping was quantified using two features: FirstQMeanErr and FirstQMaxErr. FirstQMeanErr and FirstQMaxErr computed the MAE and the maximum error between the target waveform and the patient's response during the first quarter of a sine cycle, respectively. The first quarter of the sine cycle, as annotated in **Figure 4**, was used to estimate the time period of initiating the gripping action. ThirdQMeanErr and ThirdQMaxErr were derived in a similar manner as FirstQMeanErr and FirstQMaxErr to quantify the overshooting response when releasing the grip during the third quarter. PhaseShift was designed to estimate how quickly patients reacted to correct the error caused by the overshooting response. PhaseShift computed the time to reach the grip force that was equal to the amplitude of the target waveform at the end of each quarter (i.e., 50% MVC). Since a single test contained seven sine cycles, features related to the overshooting response were averaged over the seven cycles. Muscle fatigue, which is defined as the temporary inability of muscles to perform optimally [33], was assessed using two measures: LAST-PK-SINE and ΔPK-SINE. LAST-PK-SINE computed the peak amplitude of the patient's response during the last sine cycle. ΔPK-SINE computed the difference in the peak amplitudes between the first and the last sine cycles. Tremor was quantified using the following three features, which were all computed in the frequency domain: 2ndFreq, ΔFreq, and ΔGain. 2ndFreq computed the frequency with the second largest gain after the fundamental frequency of the patient-generated waveform; the fundamental frequency should be very close to that of the target waveform (i.e., 0.16 Hz). ΔGain was the gain difference between the two frequencies. ΔFreq computed the difference between the fundamental frequencies of the target waveform and the patient-generated waveform.

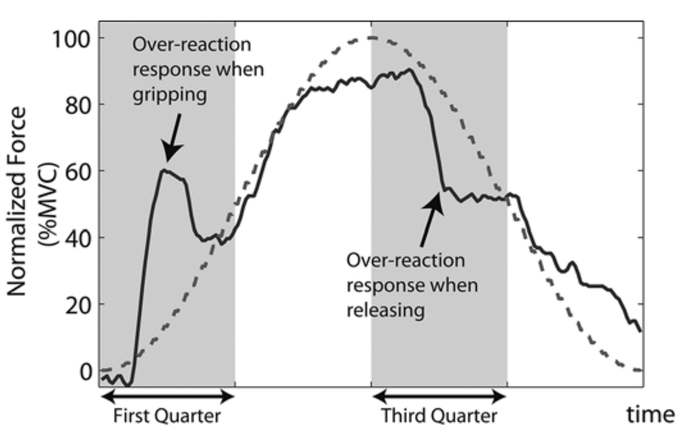

Figure 4.
Example of over-reaction responses that are illustrated with a sudden peak at the initiation and a sudden drop at the releasing of grip forces. MVC = maximum voluntary contraction.

Step waveform. A total of 12 features were extracted from the step waveform. MAE (MAE-STEP) was computed to represent the comprehensive motor capacity under step waveform. VEL-INC, AMP-INC, VEL-DEC, and AMP-DEC were used to investigate how fast a patient can exert and release the submaximal grip force. VEL-INC calculated the velocity of the grip force (% MVC per second) when switching from the lowest (20% MVC) to the highest grip force (80% MVC). AMP-INC represented the maximum difference in the amplitudes during this initiation phase of gripping. VEL-DEC and AMP-DEC were computed in a similar manner when releasing the grip force. Muscle endurance, defined as the ability to sustain repeated contractions against a resistance for an extended period of time [33], was quantified using AVG-HIGHEST, STD-HIGHEST, AVG-LOWEST, and STD-LOWEST. AVG-HIGHEST and STD-HIGHEST computed the mean and the standard deviation of the amplitude of the patient's waveform while maintaining the highest grip force (80% MVC). Similarly, AVG-LOWEST and STD-LOWEST computed the mean and the standard deviation when the subject was maintaining the lowest grip force (20% MVC). Muscle fatigue was assessed similarly to that of the sine waveform. LAST-PK-STEP computed the mean amplitude of the patient's response during the highest grip force (80% MVC) of the last step cycle. ΔPK-STEP computed the difference in the mean amplitudes of the highest grip force between the first and last step cycles.

Eliminating Unreliable Features

Employing a preprocessing step that examined the test-retest reliability eliminated unreliable features, as introduced in Palmerini et al. [34]. The features extracted from the last two (out of three) tests were used to compute the intraclass correlation coefficient (ICC); the first test was considered a practice trial and was not included in the reliability test. The value of the ICC ranged from 0 to 1, where an ICC < 0.4 indicated poor test-retest reliability, $0.4 \le$ ICC < 0.75 indicated fair to good test-retest reliability, and an ICC ≥ 0.75 indicated excellent test-rest reliability [35]. The ICC values were computed separately for the control, the preoperative CSM, and the postoperative CSM data sets. The features that produced ICC < 0.75 for any of these three data sets were removed from further analyses. This ensured a reliable quantification of motor impairment, since the decision function (i.e., kernel function) of a classifier or a regressor was constructed by mathematically combining features that were test-retest reliable. Palmerini et al. provides more detailed information on this method [34].

Feature Selection

We utilized a wrapper approach for feature selection that evaluated all feature subsets within its feature searching space for their classification/regression performance and selected the subset that produced the best performance [36]. First, the maximum cardinality of a feature subset was constrained based on the data set-to-feature ratio, as suggested by Prichep et al. [37]. For a linear classification model, the minimum data set-to-feature ratio was limited to 10:1, and for a quadratic model, the cardinality of the selected feature set (denoted as F) was limited such that $F \times (F + 3) / 4$ did not exceed the number of subjects of the smallest class [37]. A forward selection was used to construct the feature searching space. The forward selection approach started with an empty feature set and progressively added a feature that produced the best classification/regression performance until its size reached the defined maximum cardinality. Note that the same classifier/regressor, which was followed to address the objective, was used to compute the classification/regression performance. Another layer of a LOSOCV was employed within the training set to evaluate each feature subset throughout the forward selection. The selected feature sets were then used to construct a classification/regression model to address each of the three objectives, which are discussed in the following subsections.

Detection of Impairments in Hand Motor Function

In order to detect the presence of hand motor impairments in patients with CSM, we formulated the impairments problem as a binary classification problem between the handgrip data of 30 preoperative patients with CSM and 30 age-matched control subjects. This allowed us to construct an equation using the selected features to maximize the probability of distinguishing the two groups and thus produce the binary prediction of the presence of impairment (i.e., have impairment or not?) and the severity of impairment (i.e., the posterior probability of having impairment). We investigated three different classification algorithms: support vector machine (SVM) with a linear kernel, linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA). The *c*-statistic, which is an effective technique for assessing diagnostic and predictive accuracy in disease management [38], was used to evaluate the classification performance [39]. The *c*-statistic is also known as the area under the receiver operating characteristic (ROC) curve [32] and represents the probability of a randomly selected subject being correctly predicted in his/her class (e.g., has impairment or not?). The ROC curve is a graph of the true positive rate (TPR) (sensitivity) against the false positive rate (1 – specificity), which visualizes the classification performance. The *c*-statistic ranges from 0.5 (unable to discriminate) to 1.0 (able to perfectly discriminate), where 0.8 is known to represent fairly good discriminatory ability.

The prediction results were compared to the clinical variables introduced in the "Methods: Other Clinical Variables" section in an attempt to find possible relationships between the hand motor patterns detected by the algorithms and existing clinical knowledge. More specifically, the binary predictions made on the patient (positive) data, which included true positives and false negatives, were compared to the 10 clinical variables using a *t*-test. The posterior probabilities of the predictions were also compared to the clinical information using Pearson linear correlation. The binary predictions made on the control (negative) data and their posterior probabilities were similarly compared to the nondisabled subjects' age and sex using the *t*-test and Pearson linear correlation, respectively.

Estimation of Perceived Motor Deficits

Estimating the perceived motor deficits was formulated as a regression problem between the handgrip data and the ODI scores of 30 preoperative and 17 postoperative patients. Note that estimating mJOA scores was not investigated in this work, since the values did not show much variability and were highly unbalanced toward a single score; the minimum and the maximum scores were 15 and 18, respectively, and a vast majority of the scores were 16. Furthermore, ODI has a larger number of questions that are closely related to motor functions for ADL. The regression models tested in this work include (1) support vector regression (SVR) with a linear kernel; (2) SVR with a nonlinear, radial kernel; and (3) multivariate linear regression (MLR). The maximum cardinality of a feature set was limited to $F = (30/10) = 3$ since the data involved 30 patients. The nonlinear SVR also employed this rule for convenience. The estimation accuracy was evaluated using the mean absolute difference (MAD) between the estimated and the actual ODI scores, and the p-value of Pearson linear correlation was used to test the null hypothesis of zero correlation. Then, the actual and estimated ODI scores were compared with the clinical variables using Pearson correlation in order to provide clinical interpretations.

Responsiveness

Responsiveness was formulated as a binary classification problem between the patients whose perceived motor functions improved and those whose perceived motor functions did not improve after the surgical intervention, in a similar manner to that used by Deyo and Centor [28]. The improved patients were defined as those whose postoperative ODI and mJOA scores were both improved compared to their preoperative values. In our study, 12 patients were categorized as improved and 5 patients as not improved. The maximum cardinality of a feature subset was limited to $F = (17/10) = 2$ for a linear model and $F = 3$ for a quadratic model. The difference between postoperative and preoperative values was computed for all motor features and was used as the input data. Three different classification algorithms (i.e., SVM, LDA, and QDA) were used as the models, and their classification accuracies were evaluated using the c-statistic. The binary prediction results and their posterior probabilities were compared with the clinical variables using the t-test and Pearson linear correlation in order to find clinical justification.

RESULTS

Test-Retest Reliability of System

Table 1 summarizes the features used in this work. The first column represents the symptoms of CSM that the features were designed to quantify. The second and third columns represent the name and the associated waveform, respectively. The rest of the columns summarize the mean, standard deviation, and ICC values for test-retest reliability for data sets collected from control subjects, preoperative CSM patients, and postoperative CSM patients. LAST-PK-SINE and LAST-PK-STEP showed an ICC < 0.75 for the data set collected from nondisabled subjects and were removed from any further analyses. These two unreliable features were indicated with shading in **Table 1**.

Detection of Impairments in Hand Motor Function

The ability of the system to detect the presence of hand motor impairments is summarized in **Table 2**. QDA outperformed LDA and SVM in classifying patients with CSM with hand motor impairments from control subjects, with a c-statistic of 0.89; the anticipated TPR and true negative rate (TNR) were 0.83 and 0.87, respectively. This implies that the system can discriminate between individuals with hand motor impairments and those without hand motor impairments with an average accuracy of 89 percent. The ROC curve used to compute the c-statistic is illustrated in **Figure 5**. The detection results were compared with the clinical variables, but no statistical significance was found.

The most frequently selected feature subset for QDA contained MAE-SINE, FirstQMeanErr, 2ndFreq, PhaseShift, ΔGain, and AVG-HIGHEST. These are the features that significantly contributed in achieving the expected detection accuracy of 89 percent. MAE-SINE, FirstQMeanErr, and 2ndFreq were the most significant features; each of these features showed statistical significance in differentiating the two groups: MAE-SINE showed $p < 0.001$, FirstQMeanErr showed $p < 0.003$, and 2ndFreq showed $p < 0.007$ using a t-test.

Estimation of Perceived Motor Deficits

SVR with a radial kernel produced the most accurate results in estimating the ODI score (**Table 3**). The estimated ODI scores were compared to the actual ODI scores and produced MAD = 0.12, which represents the expected estimation error rate. Furthermore, the estimated

Table 1.
A summary of hand motor features that are extracted based on the symptoms of cervical spondylotic myelopathy (CSM) and the patient-reported outcomes. Unreliable features with intraclass correlation coefficient (ICC) < 0.75 are shaded.

Associated Symptom	Feature*	Waveform	Control Subjects		CSM Patients (Preop)		CSM Patients (Postop)	
			Mean (SD)	ICC	Mean (SD)	ICC	Mean (SD)	ICC
Comprehensive Measure	MAE-SINE	Sine	6.48 (0.90)	0.97	13.55 (13.19)	0.97	9.24 (5.39)	0.96
	MAE-STEP	Step	7.49 (1.44)	0.94	13.26 (8.24)	0.99	10.24 (7.90)	0.99
Overreaction Responses	FirstQMeanErr	Sine	6.13 (1.62)	0.86	13.19 (9.89)	0.97	8.60 (7.96)	0.99
	FirstQMaxErr	Sine	22.49 (6.59)	0.79	39.56 (19.01)	0.94	26.54 (17.70)	0.97
	ThirdQMeanErr	Sine	22.49 (6.59)	0.95	8.33 (13.08)	0.94	4.01 (9.82)	0.78
	ThirdQMaxErr	Sine	1.83 (4.58)	1.00	5.35 (6.57)	0.76	1.42 (4.90)	1.00
	PhaseShift	Sine	3.02 (1.42)	0.76	12.61 (33.19)	0.99	5.77 (5.31)	0.98
	VEL-INC	Step	1.82 (0.39)	0.96	1.80 (0.57)	0.93	1.81 (0.29)	0.84
	AMP-INC	Step	66.65 (2.95)	0.92	65.59 (10.04)	0.99	64.63 (6.14)	0.89
	VEL-DEC	Step	−1.42 (0.21)	0.89	−1.46 (0.42)	0.88	−1.27 (0.16)	0.84
	AMP-DEC	Step	−66.41 (3.11)	0.94	−65.71 (10.41)	0.99	−64.03 (5.77)	0.78
Fatigue	LAST-PK-SINE	Sine	94.29 (3.63)	0.68	91.19 (10.37)	0.98	93.01 (6.42)	0.97
	ΔPK-SINE	Sine	0.58 (1.40)	0.94	−1.23 (12.12)	0.98	0.57 (2.15)	0.97
	LAST-PK-STEP	Step	82.91 (3.35)	0.52	79.24 (13.99)	0.96	81.27 (8.50)	0.80
	ΔPK-STEP	Step	1.34 (2.72)	0.77	4.71 (12.32)	0.96	1.55 (2.90)	0.99
Endurance	AVG-HIGHEST	Step	75.28 (1.56)	0.89	69.72 (7.38)	0.97	72.19 (8.96)	0.98
	STD-HIGHEST	Step	10.85 (1.95)	0.90	14.25 (6.98)	0.97	12.04 (5.15)	0.99
	AVG-LOWEST	Step	26.66 (2.75)	0.89	29.88 (6.76)	0.95	26.55 (4.30)	0.82
	STD-LOWEST	Step	12.66 (1.85)	0.89	16.49 (7.11)	0.99	13.60 (4.10)	0.94
Tremor	2ndFreq	Sine	0.33 (0.11)	0.80	0.43 (0.16)	0.96	0.39 (0.17)	0.93
	ΔFreq	Sine	0.00 (0.00)	1.00	0.00 (0.02)	0.99	0.00 (0.00)	1.00
	ΔGain	Sine	5.74 (4.31)	0.94	7.69 (5.55)	0.95	5.82 (5.85)	0.91
Patient-Reported Functional Outcomes	ODI	—	—	—	0.68 (0.23)	—	0.76 (0.17)	—
	mJOA	—	—	—	0.83 (0.11)	—	0.95 (0.06)	—

*Full descriptions of the features listed in this table can be found in the "Methods: Data Analysis, Hand Motor Features" section.
mJOA = Modified Japanese Orthopedic Association (scale), ODI = Oswestry Disability Index, Postop = postoperative, Preop = preoperative, SD = standard deviation.

Table 2.
The *c*-statistics, expected true positive rates (TPRs), and expected true negative rates (TNRs) for classifying cervical spondylotic myelopathy patients with hand motor impairments from nondisabled control subjects. Quadratic discriminant analysis (QDA) (in bold) produced superior classification performance compared to support vector machine (SVM) and linear discriminant analysis (LDA). The most frequently selected features from the cross-validation included MAE-SINE, FirstQMeanErr, 2ndFreq, PhaseShift, ΔGain, and AVG-HIGHEST.

Classifier	*c*-Statistic	TPR	TNR	Most Frequently Selected Features*
SVM	0.82	0.83	0.73	MAE-SINE ThirdQMeanErr, AVG-HIGHEST
LDA	0.87	0.83	0.83	MAE-SINE, FirstQMeanErr, ThirdQMeanErr, AVG-HIGHEST, STD-HIGHEST
QDA	**0.89**	**0.83**	**0.87**	MAE-SINE, FirstQMeanErr, 2ndFreq, PhaseShift, ΔGain, AVG-HIGHEST

*Full descriptions of the features listed in this table can be found in the "Methods: Data Analysis, Hand Motor Features" section.

ODI scores showed a statistically significant correlation to the actual ODI scores with Pearson $r = 0.76$ and $p < 0.001$. **Figure 6(a)** illustrates the scatter plot between the estimated and actual ODI scores, and **Figure 6(b)** illustrates its Bland-Altman plot, where the bias of the difference was –0.016 and the magnitude of the limit of agreement was 0.27. Clinical variables were compared with the estimated ODI scores as well as with the actual ODI scores. The arm pain duration showed statistically significant correlations to the actual and estimated ODI scores collected postoperatively, with $p < 0.006$ and $p < 0.007$, respectively.

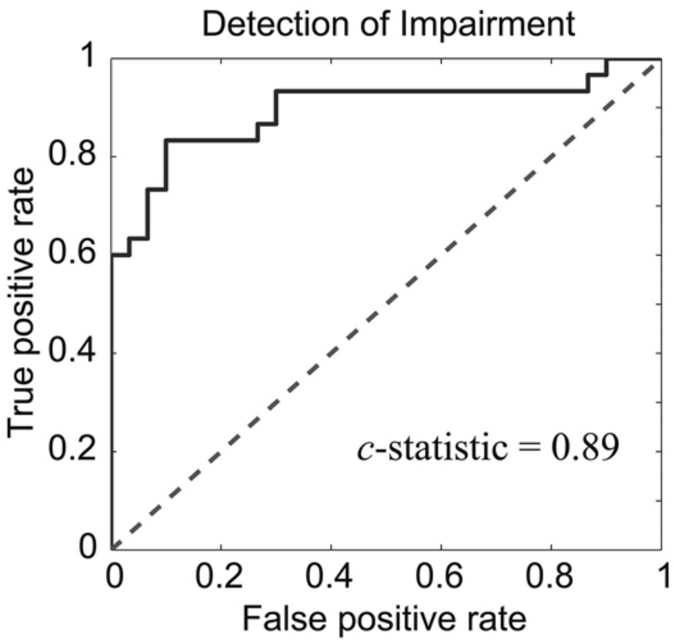

Figure 5.
Receiver operating characteristic curve for detecting the presence of impairment, generated from the quadratic discriminant analysis-based model.

The most frequently selected feature subset for this nonlinear SVR contained FirstQMeanErr, ΔGain, and VEL-INC. Among the selected features, VEL-INC was the most significant feature, with $r = 0.42$ and $p < 0.003$ when compared to the ODI scores.

Responsiveness

The ability of the system to detect patients whose perceived motor function improved (or did not improve) after the surgical intervention is summarized in **Table 4**. Linear SVM produced the best classification accuracy, with a *c*-statistic of 0.82, expected TPR of 0.92, and expected TNR of 0.80. This result shows that the handgrip system can be used to monitor the changes in perceived motor function with an average accuracy of 82 percent. The ROC curve produced by SVM is illustrated in **Figure 7**.

The classification results and their associated posterior probabilities were compared to the collected clinical variables. The overall back pain duration showed statistically significant correlation to the prediction results and posterior probabilities with $p < 0.004$ (*t*-test) and $p < 0.008$ (Pearson linear correlation), respectively. This shows that the surgical outcome predicted by the handgrip device has a significant correlation to back pain duration.

The most frequently selected feature set included ThirdQMeanErr and AVG-LOWEST. The changes in ThirdQMeanErr scores for the improved and the not-improved groups were –4.41 and 5.24 ($p < 0.004$ [*t*-test]), respectively, which implies that ThirdQMeanErr values for the improved group significantly improved after the surgery compared with the not-improved group. In a similar manner, the improvement in AVG-LOWEST was –3.03 for the improved and –0.77 for the not-improved group ($p < 0.08$ [*t*-test]).

DISCUSSION

The aim of this pilot study was to validate the use of the target tracking test in (1) detecting the presence of hand motor impairment, (2) estimating the ODI scores reported by patients, and (3) detecting changes in perceived motor deficits in performing ADL (i.e., responsiveness). These objectives were performed in a test-retest reliable manner by employing a preprocessing step that eliminated unreliable features. The reported results showed acceptable accuracy in detecting the presence of hand motor impairment and in the responsiveness; results demonstrated that the system might be considered for use as a screening tool prior to surgical treatment and as a tool to monitor ailment

Table 3.
Expected estimation performance based on mean absolute difference (MAD), coefficient of determination (R^2), and Pearson correlation coefficient (*r*). Support vector regression (SVR) with a radial kernel (in bold) produced the best estimation results compared to multivariate linear regression (MLR) and SVR with a linear kernel. The most frequently selected features from the cross-validation included FirstQMeanErr, ΔGain, and VEL-INC.

Classifier	MAD	R^2	*r*	Most Frequently Selected Features*
MLR	0.14	0.37	0.61	ThirdQMeanErr ΔGain, AMP-INC
SVR: Linear	0.14	0.27	0.54	ThirdQMeanErr ΔGain, AMP-INC
SVR: Radial	**0.12**	**0.57**	**0.76**	FirstQMeanErr ΔGain, VEL-INC

*Full descriptions of the features listed in this table can be found in the “Methods: Data Analysis, Hand Motor Features” section.

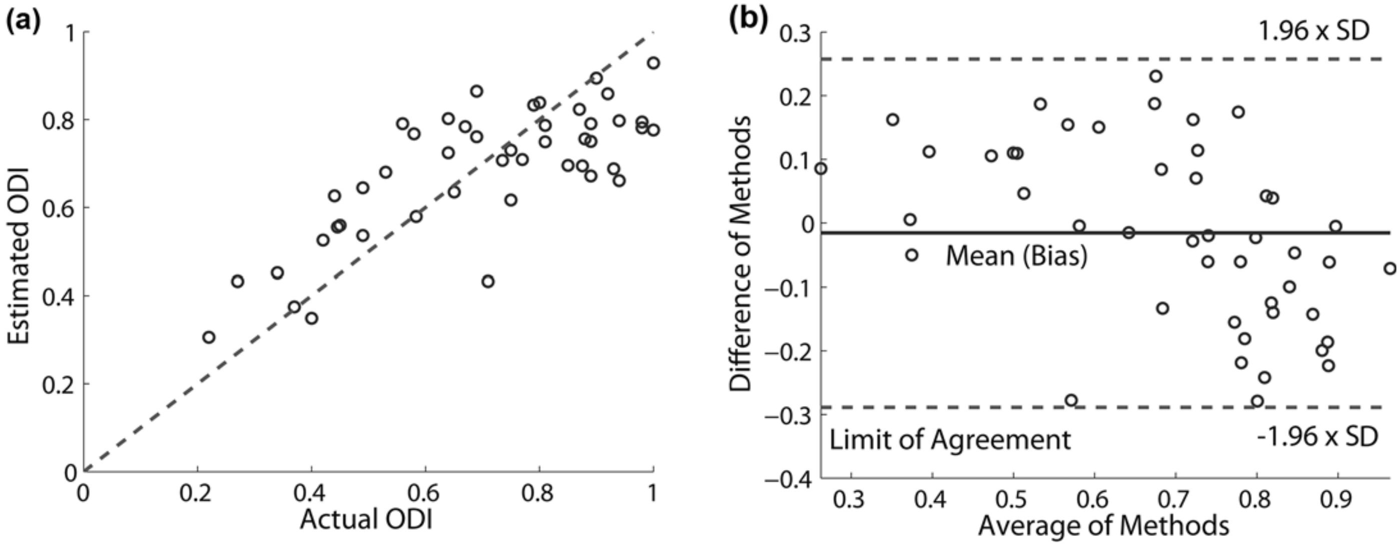

Figure 6.
(a) Scatter plot of the estimated and actual Oswestry Disability Index (ODI) scores, which achieved mean absolute difference = 0.12, Pearson r = 0.76, and p < 0.001. **(b)** Bland-Altman plot of the estimated and actual ODI scores, which achieved a bias of –0.016 and a limit of agreement of 0.27. SD = standard deviation.

Table 4.
The *c*-statistics, expected true positive rates (TPRs), and expected true negative rates (TNRs) for classifying improved and nonimproved patients after surgical operation. Support vector machine (SVM) with a linear kernel (in bold) produced the best performance compared to quadratic discriminant analysis (QDA) and linear discriminant analysis (LDA). The most frequently selected features from the cross-validation included ThirdQMeanErr and AVG-LOWEST.

Classifier	*c*-Statistic	TPR	TNR	Most Frequently Selected Features*
SVM	**0.82**	**0.92**	**0.80**	ThirdQMeanErr, AVG-LOWEST
LDA	0.76	0.92	0.60	ThirdQMeanErr, STD-LOWEST
QDA	0.76	0.92	0.60	ThirdQMeanErr, AVG-LOWEST

*Full descriptions of the features listed in this table can be found in the "Methods: Data Analysis, Hand Motor Features" section.

progress over time. The system is easy-to-use and inexpensive, and it takes no more than 5 min to complete a test, which also supports the system's potential to remotely monitor patients in their home and community settings. Estimation of the ODI scores did not show outstanding performance, but the results were comparable to other works. The following subsections will provide detailed discussion regarding each study objective as well as their limitations and planned future work.

Test-Retest Reliability

The results summarized in **Table 1** support the test-retest reliability of the motor features extracted from the handgrip device. A total of 22 features were extracted, and 20 of them showed excellent test-retest reliability in both control and patient groups. This indicates that the target tracking test provides reliable representation of one's hand motor function. Two features in the control group did not show good test-retest reliability: LAST-PK-SINE and LAST-PK-STEP, which computed the peak amplitude of the patient's response during the last cycles of the sine and step waveforms, respectively. The most likely reason for this unreliability is that the peak value may be too sensitive to a single value that overrepresents the patient's response during the last cycle. Two patients produced outlying peak values for each of the two features and significantly reduced the ICC. Consequently, these two features were removed from further analyses to ensure the reliability of

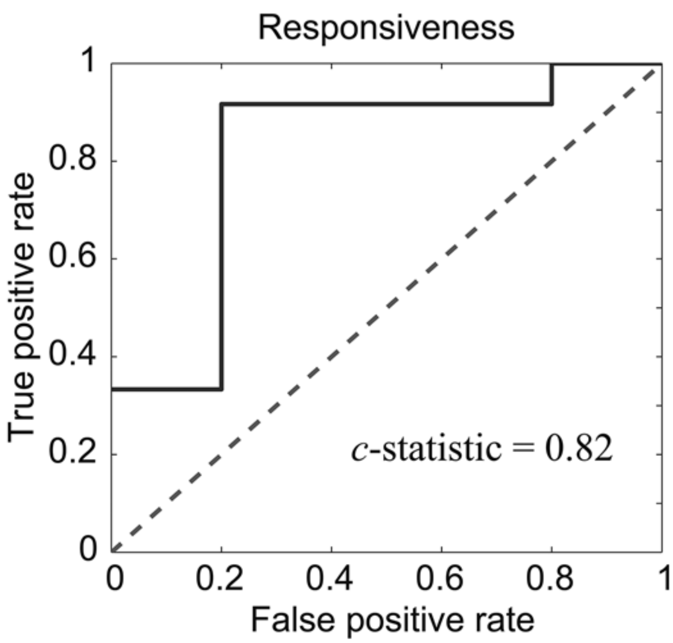

Figure 7.
Receiver operating characteristic curve produced by support vector machine for detecting the changes in physical conditions of patients after surgical operation.

the classification and regression models for the three objectives.

Detection of Impairments in Hand Motor Function

Results summarized in **Table 2** show that the handgrip system can detect the presence of motor impairments in hand movement with an average accuracy of 89 percent (with a TPR of 83% and a TNR of 87%). This indicates that the system has the potential to be used as a diagnostic tool for the CSM population. The reported detection accuracy could be achieved by employing QDA with the following features: MAE-SINE, FirstQMeanErr, 2ndFreq, PhaseShift, ΔGain, and AVG-HIGHEST. Among these features, MAE-SINE, FirstQMeanErr, and 2ndFreq were the most significant features; each individual feature showed statistically significant diagnostic ability in differentiating the CSM and control groups. This suggests that if a clinic has a limited access to advanced algorithms such as QDA, investigating these three features can also provide insights regarding the presence of hand motor impairments.

The detection results showed that five patients were incorrectly classified as having no impairments in hand motor function and four control subjects were incorrectly classified as having hand impairments. These results were compared with various clinical variables ("Methods: Other Clinical Variables" section), but no statistical significance was found. This implies that the objective quantification of the hand motor impairment, obtained by employing the handgrip system and the algorithms, provides unique information that cannot be found in other clinical variables. Thus, we propose that the system can be used as part of diagnostic and screening processes to quantify the level of hand motor function.

Estimation of Perceived Motor Deficits

The handgrip system could estimate the ODI scores in patients with CSM with moderate accuracy, namely MAD = 0.12 and $r = 0.76$ (**Table 3**). This is not surprising since the handgrip device quantifies patients' hand motor functions and ODI quantifies the degree of interference of motor impairments in performing various ADL. Nevertheless, the reported correlation results ($r = 0.76$) were comparable to the findings in other studies. In Grönblad et al., the ODI was compared to the Pain Disability Index and the Visual Analog Scales for pain and achieved $r = 0.83$ and $r = 0.62$, respectively [40]. Furthermore, the ODI was compared to the McGill Pain Questionnaire [26], Short Form-36 [41], and Roland-Morris questionnaire [25], and achieved $r = 0.62$, $r = 0.77$, and $r = 0.66$, respectively. Specifically, in Fairbank and Pynsent [7], the Bland-Altman plot between ODI and Roland-Morris showed that the magnitude of the limit of agreement was approximately equal to 0.32, which is comparable to the limit of agreement reported in this work (i.e., 0.27 as shown in **Figure 6**). Note that the correlation results reported in the aforementioned works [25–26,40–41] used the original ODI scores, which used the scale between 0 and 50, where 0 represented completely nondisabled and 50 represented completely disabled conditions. On the other hand, this work used a reversed scale that ranged from 0 (completed disabled) to 1 (completely nondisabled) as discussed in the "Methods: Patient-Reported Functional Outcomes" section. Nonetheless, the reported results demonstrate that the handgrip device and algorithms can together quantify the hand motor function with close correlation to the level of perceived deficits in performing ADL with acceptable accuracy. The estimated ODI scores, as well as the actual ODI scores that were collected postoperatively, showed statistically significant correlation to arm pain duration ($p <$

0.007 and $p < 0.006$, respectively), which agrees with findings in prior work [42].

Table 3 shows that SVR with a radial kernel, which is a nonlinear regression model, performs better than the two linear models (MLR and SVR with a linear kernel). This demonstrates that the relationships between the predictors and the ODI scores can be more accurately described using nonlinear functions, which partially agrees with the findings in Hoffman et al. [42]. The reported estimation accuracy (MAD = 0.12 and $r = 0.76$) can be achieved when FirstQMeanErr, ΔGain, and VEL-INC are used to construct an SVM-based model. However, if a clinic has limited access to such an advanced regression algorithm, it can also utilize VEL-INC as an estimation factor since it produced a statistically significant correlation to ODI scores with $r = 0.42$ and $p < 0.003$.

Responsiveness

Results shown in **Table 4** demonstrate that the handgrip device can classify patients whose perceived motor function has improved after their surgical intervention with an average accuracy of 82 percent (the TPR was 92% and the TNR was 80%). This supports that the handgrip device and the target tracking examination have the potential to be used as a monitoring tool that tracks longitudinal changes in perceived motor function. The reported classification accuracy can be achieved by computing ThirdQMeanErr and AVG-LOWEST and constructing a classification model using a SVM with a linear kernel. ThirdQMeanErr showed statistical significance in differentiating the improved and not improved groups ($p < 0.004$ [*t*-test]). Thus, if a clinic has limited access to sophisticated algorithms such as SVM, healthcare professionals can investigate the values of ThirdQMeanErr, which can be easily computed from the handgrip device.

The classification results and the associated posterior probabilities showed statistical significance to the overall back pain duration with $p < 0.004$ (*t*-test) and $p < 0.008$ (Pearson linear correlation), respectively. It is especially interesting that the results showed significant correlation to the overall back pain duration rather than the arm or neck pain. This may be because major symptoms of CSM include not only deterioration of hand use but also difficulty in gait; a previous study shows that approximately 75 percent of patients with CSM experience deterioration of hand motor function and 80 percent experience difficulty in gait [43]. Therefore, the overall back pain duration, which is a major prognostic factor for surgical outcomes [44], shows significant correlation to the predicted surgical outcomes.

Limitations and Future Works

This work is the first study to thoroughly evaluate the use of a handgrip device for detecting the presence of ailments, estimating the perceived motor function represented by ODI scores, and measuring the responsiveness to the surgical intervention in patients with CSM. Some limitations deserve discussion. The small sample size makes it difficult to generalize our findings to the general CSM population. However, all the classification and regression performances reported in this article were computed using the LOSOCV technique, which produced a fair estimate rather than an optimistic estimate [32]. Given this, the results reported in this article are promising.

The ODI was employed to represent the perceived motor deficits in performing ADL; ODI scores were estimated using the features extracted from the target tracking tests. As noted previously, both the ODI and mJOA were collected from the participating patients, but only the ODI was used in this work because the mJOA scores of the patients were highly unbalanced. The ODI investigated the degree of interference from pain in performing a number of ADL involving both upper and lower limbs. The ODI has been widely used to assess functionality of patients with CSM in a number of previous studies [7,22,42,45–46], because a vast majority of patients with CSM have complaints about the use of their hands (upper limb) as well as difficulties in gait (lower limb) [43]. However, other patient-reported outcomes such as the Neck Disability Index (NDI) [47] may provide better correlation to hand motor skills that can be captured by the handgrip device. The current study has modified the protocol to collect ODI as well as NDI to find possible correlations, which remains as future work.

CONCLUSIONS

This article introduced a method for quantifying hand motor function using a handgrip device and target tracking tests. Data analytic methods based on machine learning techniques were designed to validate the use of the target tracking test in (1) detecting the presence of impairments in hand motor function and quantifying their severity, (2) estimating the perceived motor deficits of CSM patients that are measured by ODI using the features extracted from hand motor function, and (3) detecting the changes in physical condition (improved versus not improved) after surgical decompression by investigating the changes in hand motor function. The estimation results, which were produced from a LOSOCV-based technique, showed a *c*-statistic of 0.89 for detection of impairments, Pearson *r* of 0.76 with $p < 0.001$ for the estimation of ODI, and a *c*-statistic of 0.82 for responsiveness. This pilot study reports promising results validating the use of a handgrip device and target tracking tests to provide objective quantification of various hand motor functions. This enables new research and development opportunities for more objective, easy-to-use, and inexpensive methods to assess the level of impairment and the surgical outcomes in patients with CSM.

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