Objective Assessment of Overexcited Hand Movements using a Lightweight Sensory Device

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***Abstract*—Hyperexcitability in hand is a disorder characterized by exaggerated muscle movement, and is a common symptom associated with neuro-degenerative diseases and spinal cord injuries. Current assessment methods for hyperexcitability rely on subjective examination, or on methods that evaluate the overall hand grip performance without particularization in the excitation. This paper introduces a system that utilizes an inexpensive body sensor device combined with a series of signal processing units that extract information specifically related to physiological phenomena generated by hyperexcitability. A clinical cohort study has been conducted on nine patients with cervical spinal cord injuries (mean age 58.2 ± 13.5). The experimental results show that the proposed signal processing mechanism accurately detects and analyzes the body signal. The medical significance of the experimental results is also investigated. This opens up a new opportunity for patients and clinical professionals to obtain accurate feedback of patient's motor function in an economical and ubiquitous manner.**

I. Introduction

Patients who suffer from neuro-degenerative diseases (e.g., stroke and Parkinson's disease) or traumatic spinal cord injuries often carry movement deficits in upper extremities [1], [2]. Among many motor symptoms associated with these ailments, we are particularly interested in hyperexcitability in hand muscles, which is defined as a motor disorder characterized by exaggerated tendon jerk reflexes [3] due to an excessive velocity increase in muscle tone [4]. Handgrip hyperexcitability creates involuntary forces during grasping performance, which intensely restrict daily activities requiring sophisticated hand muscle manipulation such as eating, clothing, and bathing.

Traditional assessment methodology for hyperexcitability relied on subjective observations of muscle behavior, and as a result, many attempts have been made to objectively quantify the level of hyperexcitability. Existing solutions to quantify hyperexcitability of muscle movements have concentrated on techniques such as clinical scales, Electromyogrphic (EMG), and biomechanics. However, these techniques are often highly complicated to be deployed at clinical (or in-home) settings, large in size, and extremely expensive. As a consequence, it was not economically feasible to deploy these techniques for a large patient population, and this creates a need for an accurate and affordable assessment system [5].

Sensing platforms that can be easily deployed on the body have been actively researched and are considered as alternative approaches to diagnose, to quantify, and to rehabilitate patients with motor deficits such as in [6]. Body sensing systems utilize accurate, simple, and inexpensive sensors to collect physiological data in order to quantify motor performance [7], [8]. These characteristics allow (i) easy ways to collect sensory data either pervasively or from a simple motor task, (ii) economic deployment of the system for a large patient population, and (iii) improvement in clinical benefits for patients. Clinical benefits of body sensing systems for assessing motor abnormalities include (i) economic benefits [9], (ii) frequent and continuous measurement of motor function progress over time, (iii) quantifying the effectiveness of medical treatments, such as surgical operations or medications, and (iv) early diagnosis of motor function for potential patients.

In this paper, a low-cost system that objectively quantifies the level of hyperexcitability in hand dexterity is introduced. A term *activation hypertonia* is used to describe the hyperexcitability during voluntary grip contraction (details are provided in Section IV). The proposed system utilizes a lightweight handgrip sensory device to assess the level of activation hypertonia, which makes the system highly portable. The system provides a simple target tracking task to examine fine hand motor skills for patients with cervical spinal cord injuries [10]. The collected body signals are then analyzed by a series of four signal processing units: (i) the pre-processing unit, (ii) the abnormality (i.e. activation hypertonia) detection unit, (iii) the abnormality analytic unit, and (iv) the parameter extraction unit. The preprocessing unit performs a low-pass filter to reduce noise in the raw signals, and segments the signals into a number of subsignals. The detection unit statistically determines whether a resultant subsignal contains the outcome of the exaggerated muscle tone using machine learning algorithms. If activation hypertonia is noted, the analytic unit performs an in-depth analysis to locate important geometric points using dynamic time warping (DTW). The parameter extraction unit extracts important variables that characterize the severity of activation hypertonia. The system has been clinically tried in cohort study under collaboration with the UCLA Department of Neurosurgery in order to evaluate its performance.

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II. Related Works

Exaggerated muscle movements such as muscle overactivity and spasticity in upper limbs have been actively researched. Existing methods to quantify the level of hyperexcitability in hand muscle usually involve passive resistance (external torque) against the applied patient-generated force. In [11] and [12], torque based devices are used to quantify spastic movements in elbow flexors. Especially in [11], the authors introduced a new measurement metric based on a second order linear model of the spastic velocity in order quantify the viscous component of hypertonia. Some works combined torque-based resistance devices with EMG in order to analyze the changes in muscle tone (i.e. electric signal generated by muscles) during the spastic movement [13], [14].

Although the aforementioned works focus on measuring exaggerated muscle performance, the fundamental research objective is different from what has been discussed in this work. That is, the aforementioned works focus on muscle excitability during passive motor functions, where as the proposed system examines the exaggerated muscle behavior during voluntary grip contraction. Moreover, the aforementioned works involve apparatuses that are extremely large, expensive, and complicated to use in an in home setting, which makes the systems unsuitable for portability and which would not be scalable to a large patient population.

A recent study reports that very few measurement systems exist to quantify the level of spastic muscle during functional activity (i.e. during voluntary grip contraction or relaxation) [15]. In [15], the author uses the maximal grip strength in order to measure the level of spasticity, although the grip strength reflects the comprehensive motor performance of patients. Similarly, in [16], a case of spasticity during voluntary grip contraction is reported, and the overall grip strength has been used to generically represent the overall motor function.

Clinical scales are also frequently used to assess fine motor performance (including hyperexcitability), which are often constructed based on patient-reported surveys or observation of simple muscle performance. For example, the Modified Ashworth Scale (MAS) is the most common measurement for muscle spasticity in clinics nowadays [17], [18]. Furthermore, functional measures of hand performance such as Wolf Motor Functional Test (WMFT) have been automated to generically assess the spasticity [6], [17], [19].

However, the above methods often rely on subjective measurements (e.g., clinical scales) or on quantitative methods that represent comprehensive hand muscle movement (e.g., grip strength). On the other hand, the proposed method quantifies the degree of hyperexcitability in hand muscles based on physiological motor function observed during voluntary hand contraction. As a result, parameters from various dimensions of motor functions (i.e. grip force, time, and velocity) can be accurately analyzed. This work is an extension of an abstract [8] in which the medical significance of hyperexcitability during voluntary contraction is highlighted. This paper focuses on the signal processing techniques of the acquired body signals in order to extract information reflecting the overexcited muscle behavior.

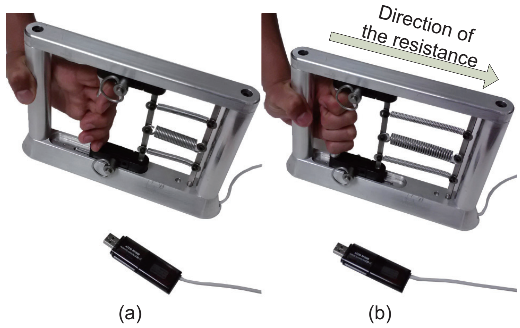

Fig. 1. (a) The digital handgrip device used in its resting position. (b) The handgrip when the handle is moved to its maximum displacement. The direction of the spring resistance is illustrated in arrows.

III. System Overview

The proposed system consists of the digital handgrip device, the software system, and the signal analytic framework. The handgrip device collects sensory data from the participating patients and delivers it to the software system. The functional objective of the software system is to guide the patient to follow the examination procedure, to provide visualized feedback, and finally to store the captured data. The captured data is then processed by the signal analytic framework in order to extract information related to activation hypertonia in hand dexterity. The digital handgrip device and the software system are discussed in detail in the following two subsections.

A. Sensory Device

The handgrip device is illustrated in Fig. 1, which is composed of three major components: the handle, the springs, and the displacement sensor.

The handle is connected to the main body of the device by three springs, which allow the patients to make voluntary grasping performance. The three replaceable springs with known constants create resistance against the direction of the grip force as shown in Fig. 1 (b). Furthermore, these springs allow the system to be calibrated to individuals with different ranges of maximum voluntary contraction (MVC)[1]. The handle is also connected to the displacement sensor embedded in the bottom of the main body to locate the position of the handle. The spring constants and the displacement information can be combined to measure the grip strength in standard units such as $Newton$ using Hooke's law: $F = -k \cdot x$, where k is the spring constant and x is the displacement.

B. Software Framework

The software starts the examination process by performing another calibration that measures the MVC. The reason behind this additional calibration is to perform the examination that is maximally accommodated to individuals with various levels of MVC since changing springs may not provide sufficient granularity.

Upon completion of the calibration process, subjects are tasked to track a moving sinusoidal waveform by adjusting

[1]MVC is defined as the maximum voluntary grip force of an individual

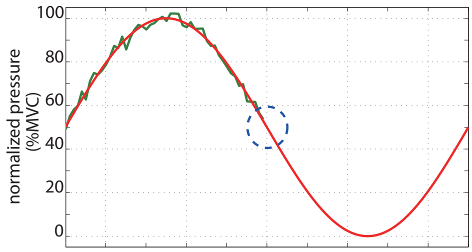

Fig. 2. Exemplary illustration of the target tracking task used in the proposed system.

their grip strength. Fig. 2 illustrates an examination provided by the software. The red sinusoidal waveform is the target waveform that moves to the left at a constant speed. The maximum amplitude of the waveform is equal to the subject's MVC as a result of the calibration process. The blue circle located in the middle of the x-axis moves freely in y-axis according to the grip strength applied to the sensory device. The green waveform appearing in the left half of the screen is real-time feedback of the subject's past performance. The examination is 45 seconds long and it contains seven sinusoidal cycles (i.e. the frequency of the sinusoidal waveform is approximately 15.6Hz), and the data is stored for post-processing.

IV. Background

An example of an instance of activation hypertonia and a normal performance is provided in Fig. 3 (a) and (b), respectively. As illustrated, the example in Fig. 3 (a) displays exaggerated muscle movement during voluntary initiation of the muscle contraction, and the example in Fig. 3 (b) shows a smooth curve without any notable shooting effect. This shooting effect is only observed among patients with hand movement deficits[2] (e.g., patients with cervical spondylotic myelopathy in this study). The term *activation hypertonia* is used to describe this physiological phenomenon, which is voluntarily initiated but not effectively controlled.

The activation hypertonia shows motor mechanism similar to hyperexcitability of the stretch reflexes in elbow or knee [4]. The exaggerated muscle movement is induced by sufficiently fast contraction velocity. Then, reactive muscle response starts to decrease the contraction velocity. For example, in Fig. 3 (a), annotation (A) represents a point where the contraction velocity is at its maximum, and this implies that the reactive muscle response is initiated to decrease the contraction velocity. At (B), the reactive response dominates the muscle movement and the spike starts to decrease. Finally at (C), the motor performance is adjusted to the target waveform.

Important parameters that characterize the exaggerated muscle behavior can be computed if geometric annotations (B) and (C) are accurately located. Thus, the proposed signal processing focuses on detecting the appearance of such an abnormal hand movement and accurately locating these important geometric annotations. The signal processing framework is composed of a series of four sub-units: (i) the pre-processing unit, (ii) the abnormality detection unit, (iii) the in-depth analytic unit that annotates the important geometric points, and (iv) the parameter extraction unit. A graphical summary of the signal processing framework is provided in Fig. 4.

[2]The shooting effect has been sometimes observed among healthy subjects with age greater than 80. However, the amplitude of the shooting was minor and not comparable to the ones generated by patients.

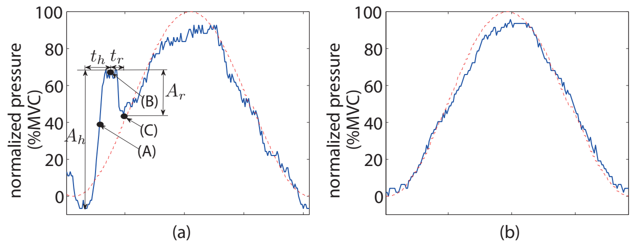

Fig. 3. (a) An example of the exaggerated muscle movement during voluntary contraction. (b) An example of a typical normal muscle behavior.

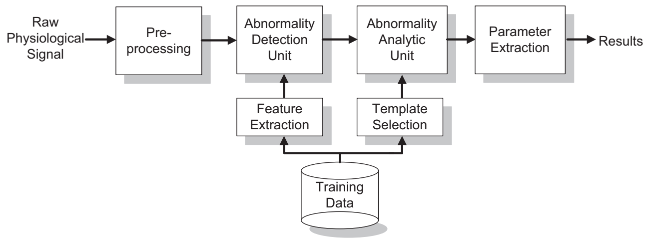

Fig. 4. Graphical overview of the signal processing framework.

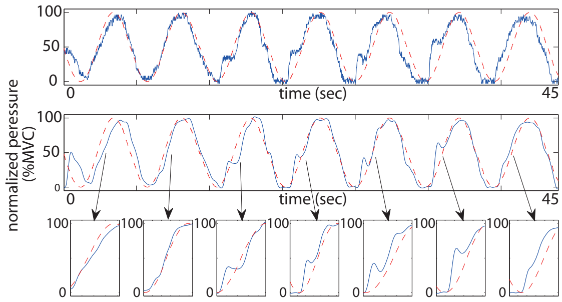

Fig. 5. An example of the results of the pre-processing unit. (Top) The raw input time-series. (Middle) The low-pass filtered time series. (Bottom) The partitioned subsignals representing muscle contraction.

V. Quantification of Activation Hypertonia

A. Pre-processing Unit

The pre-processing unit performs a fifth-order butterworth low-pass filter in order to smooth out the signal. This process allows the geometric shape of the signal to be visualized more clearly and improves the accuracy of annotating important geometric points within the signal. The cut-off frequency is set to 18Hz given that the sample frequency is 32Hz and the frequency of the sinusoidal waveform is 15.6Hz. Then, the filtered time-series signal, which contains seven sinusoidal cycles, is partitioned into seven subsignals that represent muscle contraction (i.e. rising parts of the sinusoidal waveform where its derivative is greater than zero). An example of the results of the pre-processing unit is illustrated in Fig. 5 in order to help visualization.

B. Abnormality Detection Unit

The detection unit utilizes a machine learning algorithm to detect the appearance of the exaggerated muscle performance. For example, in Fig. 5, only the third to sixth segments contain instances of activation hypertonia, and thus the analysis should be performed limited to these segments.

A total of six features are extracted to be used in the classification process. These features represent variables that generically differentiate the geometric shape of the signals with and without the exaggerated muscle behavior. The first feature is the maximum velocity of the signal (i.e. maximum amplitude of the derivative). The second feature computes the difference between the maximum and the minimum velocity. The third feature considers the number of local maxima found in the patient's response. The fourth and fifth features compute the maximum amplitude and the relative location (to the length of the segment) of the local maxima, respectively. The sixth feature computes the mean absolute difference between the patient's response and the target sine waveform since the segments containing exaggerated muscle performance usually have higher error rate. The proposed system employs a binary Support Vector Machine (SVM) for the classification algorithm. The classification of a new signal detects whether the signal contains the exaggerated muscle performance or not.

C. Abnormality Analytic Unit

The abnormality analytic unit employs a dynamic time warping (DTW) algorithm in order to extract the information about the geometric annotations discussed in Section IV (e.g., (A), (B), and (C) in Fig 3 (a)). The subsignal containing an instance of activation hypertonia is compared against a template that best represents the exaggerated muscle performance in the training data[3]. A template selection technique, which is similar to the work introduced in [20] and [21], is performed to choose a representative template.

The template selection technique is constructed as follows. The output template is denoted as T. Further, D represents a subset of the subsignals within the training data that contain instances of the activation hypertonia. A single subsignal in D is represented as τ_i, where $1 \leq i \leq |D|$. Then, the template selection starts its process by constructing a matrix M that represents the unnormalized distance between all segments in D:

$$M_{i,j} = dist(\tau_i^{'}, \tau_j^{'}),$$

where $\tau^{'}$ is the derivative of the subsignal τ, and $dist(\tau_i^{'}, \tau_j^{'})$ is the unnormalized distance between the warped subsignals $\tau_i^{'}$ and $\tau_j^{'}$. The DTW is performed on the derivative of a signal because hyperexcitability of contraction is known to depend on velocity, and the geometric annotations are also highly relevant to the derivative. Note that M is a symmetric matrix ($M_{i,j} = M_{j,i}$) and its diagonals are equal to zero since the distance between two identical signals is zero ($M_{i,i} = 0$).

Then, the template T is selected to be the subsignal that has the minimum average distance to all other signals:

$$T = \underset{i \in D}{\text{argmin}} \frac{1}{|D| - 1} \sum_{j \neq i \in D} M_{i,j}, \tag{1}$$

where $|D|$ is the total number of subsignals in D.

Given that the training signals are all annotated for their important geometric points, the result of the DTW between the template and the testing subsignal can easily locate these points by warping. Note that all signals are height-normalized (to the one with shorter height) before the DTW.

D. Parameter Extraction Unit

The parameter extraction unit computes the parameters that characterize activation hypertonia as discussed in Section IV. A total of six parameters are extracted using the geometric annotations computed as a result of the abnormality analytic unit.

The six parameters are labeled as A_h, t_h, v_h, A_r, t_r, and v_r. A_h and t_h represent the maximum amplitude and the time required to reach the peak of the hyperexcitability, respectively. Since the hyperexcitability of contraction or stretch reflexes are known to depend on velocity, the velocity to reach the peak is also an interesting parameter ($v_h = A_h/t_h$). Similarly, A_r, t_r, and v_r represent the reactive response amplitude, the time required to reach the local minimum, and the associated velocity ($v_r = A_r/t_r$), respectively. A graphical example of these parameters is provided in Fig. 3 (a).

VI. Experimental Results

A. Clinical Cohort Study

The examination procedure has been approved by the local institutional review board. The trial has been conducted for 12 months on 9 patients (mean age of 58.2 with standard deviation of 13.5) with Cervical Spondylotic Myelopathy (CSM). CSM compresses the spinal cord in the cervical area and causes hand movement deficits such as loss of hand dexterity, weakness, and coordination problems. All participated patients received a surgical spinal decompression, which decompresses the pressure applied on the pinched nerves.

Patients have participated in the study at least once prior to the operation and at one week, one month, and three months following the operation. At each clinical visit, patients performed the tracking examination exactly three times, which resulted in a total of 141 examinations. As discussed in V-A, each tracking result produces seven subsignals. However, the very first subsignal for all examination results have been discarded from the analysis since some patients started the examination while holding the blue circle in the middle and some just left the circle at zero, which produced unnecessary diversity in its geometric shape. As a result, a total of $846 = 141 \cdot 6$ subsignals were considered in this analysis. Among 846 signal subsignals, $|D| = 186$ ($\approx 22.0\%$) signals showed the exaggerated muscle movement, and they all have been annotated for the important geometric points.

[3]Note that this training data is identical to the training data discussed in Section V-B

TABLE I. CLASSIFICATION RESULTS OF THE LEAVE-ONE-PATIENT-OUT CROSS VALIDATION.

Patient ID	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	Average
TP Rate	0.98	0.97	0.97	1.00	1.00	1.00	1.00	1.00	0.98	0.99
TN Rate	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

B. Results of the Analytic Framework

This section presents the experimental results of the technique discussed in Section V. A leave-one-patient-out cross validation is used to evaluate the performance of the proposed method without polluting the results in (i) detecting the appearance of activation hypertonia and (ii) locating the important geometric annotations.

The classification results for detecting the appearance of activation hypertonia are summarized in Table I. In this table, *TP Rate* and *TN Rate* represent true positive and true negative rate, respectively, and the positive class is defined as the signals that contains the exaggerated muscle behavior and the negative class as the signals with normal muscle behavior.

When the system detects the appearance of the exaggerated muscle behavior in the signal, it performs the DTW using a template computed by Eq. (1). It is interesting to note that a signal belonging to P_6 is selected as a template for all cross-validations except for P_6. When P_6 was examined as the left-out patient, a signal that belongs to P_1 was selected as its template. This shows the robustness of the results of the proposed system in terms of its consistency in its geometric shape that the same template was chosen for all data (except one case for the left-out patient P_6). The DTW annotated the important geometric points with 99.5% ($= 185/186$) accuracy for all results. Only one signal has been mis-annotated for its unusual geometric shape. Some of the correctly annotated as well as the one incorrectly annotated result are illustrated in Fig. 6.

C. Significance of the Analysis

In the previous section, we demonstrated the accuracy of the method to detect the appearance of activation hypertonia and to annotate important geometric points. In this section, the medical significance of the computed results is validated by comparing them to the physical condition of the patients.

First of all, the six parameters discussed in Section V-D are computed for all subsignals that contain an instance of the exaggerated muscle behavior. Then, the parameter values are averaged among examination results produced per clinical visit. For example, three examinations are performed per clinical visit, and six subsignals are produced per examination. Thus, each parameter can be computed by averaging the values of at most 18 subsignals containing the exaggerated muscle performance. Addition to the six parameters, one more parameter, which counts the number of subsignals that contain the exaggerated muscle behavior, is considered.

Then, parameter values obtained before the surgical operation and the parameter values collected three-month or later after the operation are compared in terms of percentage of improvement. Suppose that ρ_i^{pre} and ρ_i^{post} represent the preoperative and postoperative values of the parameter i ($1 \leq i \leq 7$), respectively. The percentage of improvement is computed as $PI_i = \left(\rho_i^{post} - \rho_i^{pre}\right) / \rho_i^{pre}$.

Patient's also have evaluated their improvement in motor function using Oswestry Disability Index (ODI), a validated motor functional scale [22]. According to [23], the patients with ODI ≥ 0.6 are considered to in the *functional* group, and the patients with ODI < 0.6 to be in the *non-functional* group. The functional group is defined as those subjects whose comprehensive motor performance is close to that of healthy subjects, and the non-functional group is defined as whose motor performance is relatively disabled. All patients were categorized as non-functional patients prior to the surgical operation. After the operation, seven out of the nine patients showed improvement in their motor functions and were categorized as functional patients according to their ODI. Furthermore, qualitative interviews also supported that the surgical operation was successful for those seven functional patients and thus improved their motor functions.

The changes in values of the seven parameter computed by the proposed analytic framework before and after the operation have been compared against the postoperative patient's motor condition (i.e. ODI). Out of the seven parameters, v_r, which represents the muscle response velocity to recover from the spastic movement, showed the strongest correlation to the postoperative ODI values (p-value < 0.029) as summarized in Table II. Intuitively, this result shows that the reactive velocity against the spastic movement has been increased for the patients whose surgical operation has successfully improved their overall muscle performance, and the velocity has been decreased for the patients whose surgical operation was not successful. This is strong evidence that the proposed system (i.e. the handgrip device and the analytic framework) can successfully quantify the functional improvement or degradation as a result of medical treatment.

VII. FUTURE WORK AND CONCLUSIONS

This paper introduces a highly portable system that accurately quantifies the level of overexcited hand movement during voluntary hand contraction. The system utilizes a lightweight sensing platform and a signal processing framework composed of a series of four sub-processing units. A clinical cohort study has been conducted to validate the system on nine patients with cervical spinal cord injuries who have hand movement deficits, and the effectiveness of the system has been validated through an in-depth analysis. The results show that the proposed system can be useful for quantifying the level of activation hypertonia and measuring the functional progress at a low cost. Further, frequent and continuously tracking of motor performance over time may be used in the clinic or home settings to assess the need for clinical intervention or to predict the surgical success.

There exist many potential research directions to be pursued in the future. For example, analyzing voluntary reflexion in addition to contraction may provide more dimensions in motor characteristics of patients. Furthermore, utilizing a waveform that requires faster contraction or reflexion velocity,

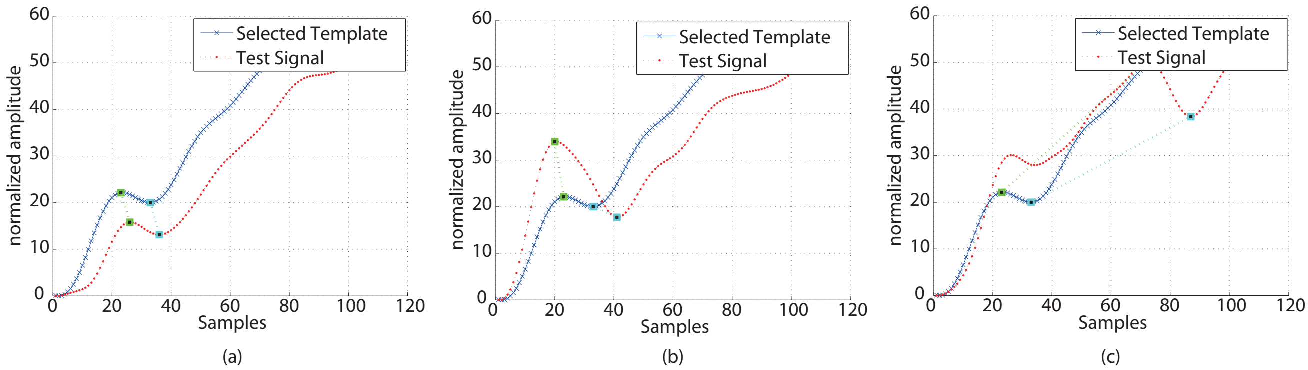

Fig. 6. Examples of the results of the analytic framework. (a) Correctly annotated result of the test signal that is has similar dynamic geometric shape as the template (b) Correctly annotated result of the test signal that has more dynamic placement of the annotation compared to the template. (c) Incorrectly annotated signal due to an additional peak

TABLE II. A SUMMARY OF THE RELATIONSHIP BETWEEN THE REACTIVE RESPONSE VELOCITY AND THE PATIENT REPORTED POSTOPERATIVE ODI.

	Functional							Non-Functional	
Patient ID	P1	P2	P3	P4	P5	P6	P7	P8	P9
ODI	0.81	0.84	0.75	0.52	0.84	0.84	0.89	0.36	0.31
P.I of v_r	0.31	0.26	0.39	0.49	0.54	0.17	0.78	-0.27	-0.33

such as a step function, may be useful to investigate the response of patients against the excited movement.

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