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Trust Sensor Interface for Improving Reliability of EMG-based User Intent Recognition

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***Abstract*— To achieve natural and smooth control of prostheses, Electromyographic (EMG) signals have been investigated for decoding user intent. However, EMG signals can be easily contaminated by diverse disturbances, leading to errors in user intent recognition and threatening the safety of prostheses users. To address this problem, we propose a trust sensor interface (TSI) that contains 2 modules: (1) abnormality detector that detects diverse disturbances with high accuracy and low latency and (2) trust evaluation that dynamically evaluates the reliability of EMG sensors. Based on the output of the TSI, the user intention recognition (UIR) algorithm is able to dynamically adjust their operations or decisions. Our experiments on an able-bodied subject have demonstrated that the proposed TSI can effectively detect two types of disturbances (i.e. motion artifacts and baseline shifts) and improve the reliability of the UIR.**

I. INTRODUCTION

There are over 1.9 million amputees in the US [1], whereas most mechanical controlled prostheses are cumbersome. Researchers are investigating how to recognize users' intent from Electromyographic (EMG) signals, which enables more natural and smooth control of prostheses [2].

Various dynamic signal processing strategies [3] and pattern recognition (PR) algorithms [4] are proposed for user intent recognition (UIR), and they can achieve high accuracy if the recorded EMG signals have good qualities. However, EMG signals can be easily contaminated by various disturbances originated in electronics equipments, at electrode-skin contact, and in ambient environments [5]. These disturbances may interfere the recorded EMG signals, cause sensor failures, and even lead to errors in the UIR. These errors may cause stumbles and falls of the amputees [4].

Most of current studies remove disturbances at three different parts of the UIR systems: (1) in electronics equipments by modern electronic technologies and appropriate circuit design [6]; (2) at the sensor-skin interface by locating and securing the EMG sensor to the skin [7]; and (3) on recorded EMG signals by either filtering out disturbed frequencies [8], [9] or removing the contaminated EMG sensors [10]. The first two categories are both pre-set and hard to be dynamically adjusted to handle diverse disturbances during usage. Although it is possible for the two methods in the 3rd category to be applied during usage, they both have disadvantages. (a) Since many disturbances overlap EMG signals at low frequencies, it is difficult for the filtering method to completely remove disturbances without impairing the original EMG signals. (b) The arbitrary removing of a sensor may reduce the accuracy of the UIR and will increase the workload by retraining the classifiers in the UIR.

In this paper, we propose a trust sensor interface (TSI) that contains two modules. An **abnormality detector** module is designed to monitor EMG signals. It can detect sudden disturbances (e.g. motion artifacts), gradually changing disturbances (e.g. gradually changing baseline noise) and even unknown disturbances, with high accuracy and low latency. Parameters of the detector are dynamically adjusted to fit variations in disturbances. Each time when a disturbance is detected on an EMG sensor, the **trust evaluation** module is applied to estimate the sensor's trust value (i.e. how reliable it is), based on its "disturbance history" (e.g. disturbance type/severity, occurrence time/number). The readings from this sensor will only be eliminated when its trust value drops below a threshold.

As a summary, the proposed scheme uses abnormality detection and trust evaluation, a strategy different from but compatible with the previous schemes. It is particularly suitable for handling dynamic disturbances that are from various sources.

The rest of the paper is organized as follows. Section II introduces the methodology; Section III describes the experiments and prototype; and Section IV discusses the experiment results, followed by conclusion in Section V.

II. METHODOLOGY

Fig. 1 shows the structure of the proposed TSI and its relationship with the UIR module. The EMG signals, collected through multiple sensors/channels, are first pre-processed and segmented by sliding windows. In each window, key features (e.g. amplitude, number of zero-crossings, etc. [4]) of the EMG signals are extracted and fed into the UIR and the TSI modules. The UIR is employed to determine users' intent (e.g. sitting, standing, etc. [4]). And the TSI module (the dashed blocks in Fig. 1) monitors the key features from each individual sensors, detects disturbances, computes sensors' trust values, aggregates the trust results, and sends the trust report to the UIR. Based on the trust report, the UIR can then adjust its operations or decisions. The overall goal is to improve the reliability of the output of the UIR, and therefore improve users' safety. Next, we will introduce the two key components of the TSI: abnormality detection (in Section II-A) and trust evaluation (in Section II-B).

A. Abnormality Detection

1) Disturbance Type: Among all types of disturbances, *motion artifacts* and *baseline disturbances*, which occur frequently, may severely interfere EMG deciphering and are difficult to be removed [6]. Therefore, in this paper, we take these two disturbances as examples to demonstrate performance of

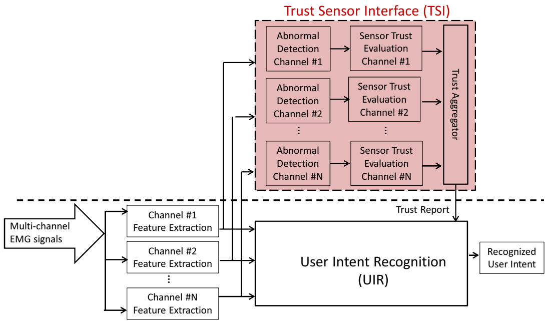

Fig. 1: Framework of Neural Machine Interface (NMI)

the proposed abnormality detector. Notice that, the proposed detector, with proper parameter settings, could handle other types of disturbances.

2) Detection Scheme: Detection of abnormality in EMG signals is a challenging problem for two reasons. (1) The type and severity of disturbances, due to environment uncertainty, can be very diverse and hard to predict. It is almost impossible to construct the training data that can represent all types of reasons behind disturbances and sensor malfunctions. (2) A fast detection is required so that the disturbance is identified before it causes severe errors in the UIR.

We propose to exploit a new EMG feature: *change*. This philosophy comes from the observation that the disturbances that cause sensor malfunctions would either introduce sudden change or gradual change in EMG signals. In other words, such changes can serve as indicators of disturbances.

There are many statistical methods to detect changes, such as these used in [11], [12]. In this work, we choose the Cumulative Sum (CUSUM) algorithm [13]. Compared with other change detectors, the CUSUM detector has three major advantages. First, it can reliably detect small shifts. Second, it is not sensitive to the probabilistic distribution of the underlying signal, which is suitable to be applied on non-stationary EMG signals. Third, it is proved to be optimal in terms of detecting changes faster than any other methods [14].

Basic CUSUM: We first introduce the basic CUSUM detector, which determines whether θ (e.g. a feature of EMG) has changed. Assume that the distributions of θ before and after change follow Gaussian distribution. The mean values of these two distributions are μ_0 and μ_1. Let y_j denote the j^{th} sample of the data sequence. The basic CUSUM decision function is

$$g_j = max(g_{j-1} + (y_j - \mu_0 - \frac{\mu_1 - \mu_0}{2}), 0) \ . \tag{1}$$

$$t_a = min\{k : g_j \geq \overline{h}\} \ , \tag{2}$$

where g_{j-1} is the decision function at the sample $j-1$, $\overline{h}$ is the threshold. Here, t_a is called *stopping time*, the time when the detector identifies a change and raises an alarm. Each time when $g_j \leq 0$ or $g_j \geq \overline{h}$, CUSUM detector restarts by setting $g_j = 0$ and a new round of detection begins. Furthermore, even if the distributions are not Gaussian, the above detector is still sensitive to mean change of θ [14].

Modified Versions of CUSUM: In basic CUSUM, it is assumed that both the mean values before and after change are known, whereas in our applications, environment uncertainty may introduce various disturbances that change the EMG signal in diverse ways. It is difficult to obtain the post-change parameters in advance. Therefore, we investigate two modified versions of CUSUM: parallel CUSUM [15] and adaptive CUSUM [16].

Since the mean value μ_1 is unknown, we use parameter k to replace the value of $(\mu_1 - \mu_0)/2$ in equation 1, and obtain

$$g_j = max(g_{j-1} + (y_j - \mu_0 - k), 0) \ . \tag{3}$$

The CUSUM detector with a smaller k is suitable for detecting smaller changes, and the one with a larger k is suitable for larger changes. A detector with inappropriate k value may either raise false alarms or not detect disturbances. Therefore, the parameter k needs to be adjusted to fit detections of different changes.

In parallel CUSUM, multiple basic CUSUM detectors are implemented simultaneously, each of which uses a different k value. The detector, whose k value is closest to $(\mu_1 - \mu_2)/2$, will first identify the change [15]. This method can capture diverse changes, but requires a higher computation cost due to the usage of multiple detectors.

The adaptive CUSUM employs only one detector. It starts with an arbitrary initial value of k. Once a disturbance is detected, this detector will estimate the amount of change according to the disturbed data, and adjust parameter k accordingly. Compared with parallel CUSUM, adaptive CUSUM greatly reduces computation cost. However, the detection delay of the adaptive CUSUM heavily relies on the initial choice of k. If the initial k is not properly chosen, many iterations will be performed before the detector converges.

Proposed CUSUM Detection: Parallel CUSUM and adaptive CUSUM both have advantages and limitations. Therefore, we propose a hybrid CUSUM scheme as follows.

1: In the initial detection stage, N basic CUSUM detectors with different k values are deployed simultaneously until the first disturbance is detected. The N value can be much less than the number of detectors in regular parallel CUSUM [15].
2: The estimation of k value is conducted based on the detected disturbed EMG signal, as in the adaptive CUSUM. Let k_0 denote the estimated k.
3: Note that there may be an offset between k_0 and the real optimal value of k. Three parallel CUSUM detectors are employed with $k = k_0$, $k = k_0 + d$, and $k = k_0 - d$, respectively. (The parameter d can be set according to different application requirements.)
4: Repeat step 2 and step 3, until the estimated k_0 does not change much or more than I interactions are performed.

Compared with the adaptive CUSUM, the proposed scheme avoids the arbitrary initial settings of k, and reduces convergence time. Compared with the parallel CUSUM, the proposed scheme reduces the computation cost.

Each type of disturbance will cause changes in different EMG features. For example, to detect motion artifacts, we apply the proposed detector on $\theta_m = mean$ and $\theta_z = zero-crossing$. Here, *mean* and *zero − crossing* are just mean and the number of zero-crossing of the EMG signal within the decision window [4]. To detect baseline shift, we apply the proposed detector to θ_m. We can also adjust the sensitivity of the detector by specifying the threshold $\bar{h}$.

B. Trust Evaluation

As discussed in Section I, once a disturbance is detected, the straightforward ways are not effective to eliminate the impact of disturbances. Therefore, we propose the trust evaluation module, which dynamically evaluates the reliability of EMG sensors based on their "disturbance history". Briefly speaking, we will reduce the trust value of an EMG sensor each time a disturbance has been detected. Disturbances that are more severe will lead to larger decreases in trust, and vice versa. If there is no disturbance detected for a long time and all previous disturbances are non-fatal, the trust value can gradually recover. If the trust value of a sensor drops below a threshold, the readings from this sensor will be removed from the UIR, until its trust recovers.

Specifically, the sensor trust value can be dynamically computed based on the beta function based trust model [17]. Given a sensor x at window i, the trust value T_i^x is calculated as

$$T_i^x = \frac{r_i^x + 1}{r_i^x + s_i^x + 2} \tag{4}$$

where s_i^x and r_i^x represent the number of windows with and without disturbances respectively.

In Equation 4, at window i, two sensors will obtain same trust value if they have same number of disturbed windows, which is not practical. For example, at window 100, both sensor 1 and sensor 2 have been disturbed in 1 window. Whereas, sensor 1 is disturbed at window 1 which is long time ago, and sensor 2 is disturbed at window 99 which is quite recent. In this case, sensor 1 should have a higher trust value since the disturbance is absent for a long time and is highly possible over. Therefore, we times the value of r_i and s_i by a forgetting factor α, where $0 \le \alpha \le 1$. In this way, the old status of a sensor takes less weights than the recent status. Furthermore, since disturbances with higher severity levels may cause more errors in the UIR, we introduce a weight factor w_i ($0 \le w_i$) to the value of s_i. w_i is proportionally determined by the disturbance severity level at window i.

Therefore, for sensor x, the values of $r_i'^x$ and $s_i'^x$ are computed as $r_i'^x = r_{old}'^x * \alpha + r_{now}'^x$ and $s_i'^x = s_{old}'^x * \alpha + s_{now}'^x \cdot w_i$, where $r_{now}'^x$ is 1 for normal window and 0 for disturbed window, and $s_{now}'^x$ is 0 for normal window, and 1 for disturbed window.

The trust value T^x, which is determined by r^x and s^x, is dynamically adjusted according to the "disturbance history" of sensor x. Once a disturbance is detected, T^x will drop. Severer disturbances will lead to larger decrease in T^x. If the disturbance lasts for a certain amount of time, T^x will continuously drop. If the disturbance stops quickly, T^x may increase again once the disturbance is over (i.e. no more disturbance is detected). When T^x drops below the threshold, sensor x will be considered as not trustworthy, and the signal recorded from it will be removed from the UIR. Meanwhile, the trust evaluation module will continue monitoring this sensor, and dynamically adjust its trust value. Of course, if the detected disturbance is fatal (e.g. EMG sensor off skin), we will use a very large w value, and make T^x directly drop below threshold and not recoverable in the future.

Compared with the straightforward detect-and-remove strategy, the proposed scheme has the following advantages. First, whether a sensor should be removed or re-enter the system depends on its accumulated trust value instead of a sudden appearance or disappearance of a disturbance. This greatly reduces (a) the frequency of re-training the classifier in the UIR due to sensors' addition or removal and (b) the impact of false alarms in disturbance detection. Second, it is possible that multiple sensors are affected by disturbances. Given the trust value of each individual sensors, we may evaluate whether the UIR faces severe risks. Obviously, when many sensors are damaged and removed, there will not be sufficient number of sensors for accurate user intent recognition. Less obviously, when most sensors remain in the system but their trust values are barely above the threshold, the UIR also faces severe risks. In the future, we will evaluate the risks faced by the overall UIR based on sensor trust.

III. EXPERIMENTS AND PROTOTYPE

A. Data Source

This study was conducted with Institutional Review Board (IRB) approval and informed consent of subjects. One male subject, free from orthopedic or neurological pathologies, was recruited. The seven monitored gluteal and thigh muscles in one side of the lower limb included the gluteus maximus (GMA), gluteus medius (GME), rectus femoris (RF), vastus lateralis (VL), vastus medialis (VM), biceps femoris long head (BFL), and biceps femoris short head (BFS). The EMG electrodes were placed over the anatomical locations described in [18]. The EMG electrodes contained a pre-amplifier, which bandpass filtered the EMG signals between 20 Hz and 450 Hz with a pass-band gain of 1000. The EMG System (Myomonitor, Delsys Inc., MA) recorded the signals with a 16 Bits signal resolution. All the signals were digitally sampled at a rate of 1000Hz.

B. Experiment Protocol

In the experiment, we collected 2 types of user intent: sitting and standing. For each type, 3 trials were conducted. In the "sit" trials, the subject was instructed to sit on a chair (60 cm high), and allowed to move legs casually. In the "stand" trials, the subject was allowed to move the legs and shift the body weight. Rest periods were allowed between trials in order to avoid fatigue. To collect pure disturbances, one trial of baseline noise and 5 trials of motion artifacts were conducted during "relax sitting" without muscle activities. The motion artifacts were generated by tapping an EMG sensor one or two times in each trial.

C. Testing Data Construction

Most current studies use two types of disturbance data: pure empirical data or pure simulation data. Empirical data is closer to reality, and usually collected for specific situations. Sometimes, it is hard to perform extensive and diverse testing purely based on empirical data. In this paper, we generate disturbance data based on empirical data with modifications.

This idea is inspired by the filter design, which attempts to separate disturbances from EMG signal by transforming the contaminated EMG signal into frequency domain and removing the disturbed frequency. We executed the procedure in a reverse direction. *First*, we collected EMG signals during sitting and standing without extra disturbances. *Second*, experiments were conducted to collect disturbances only. *Third*, we adjusted the collected disturbance data. For example, given a set of motion artifact data $x(t)$, we can generate $a \cdot x(t)$ (adjusting amplitude) where $0.5 \leq a \leq 2.5$ and t is the time. Given a set of baseline noise $y(t)$, we create gradually increasing baseline shift $b \cdot t \cdot y(t)$, where b governs how quickly the baseline shift increases. By adjusting a and b, we can obtain many different disturbance cases. *Finally*, the testing data (i.e. EMG with disturbances) was constructed by adding the adjusted disturbances and empirical EMG signals in the frequency domain and converting the addition back to the time domain. In the test, the disturbance detection will be performed in each sliding window, with window size of 150 samples and increment of 10 samples.

D. Performance Measurement

To evaluate the performance of the proposed detector, we will examine: detection rate, false alarm rate and detection delay.

For each window of the testing data, the EMG signal can be either normal (N) or disturbed (D). Meanwhile, the detector will recognize the data as either normal (N) or disturbed (D). Four scenarios are possible: (1) Hit (H): Truth = D, Detection = D; (2) False Alarm (F): Truth = N, Detection = D; (3) Miss Detection (M): Truth = D, Detection = N; and (4) Correct no detection (Z): Truth = N, Detection = N. The detection rate (DR) is calculated as

$$DR = \frac{\text{number of } H}{\text{number of } (H+M)},$$

and the false alarm rate (FA) is calculated as

$$FA = \frac{\text{number of } F}{\text{number of } (F+Z)}.$$

If it is a Hit, the detection delay (DD), which represents how long it takes the detector to detect this disturbance, is calculated as $DD = T_d - T_a$, where T_d is the time when detector detects the disturbance, and T_a is the time when the disturbance appears.

IV. RESULTS AND DISCUSSIONS

A. Impact of Disturbances on User Intent Recognition

In this section, we demonstrate the impact of gradually changing baseline and motion artifacts on the user intent recognition accuracy. The UIR module is implemented as described in [4]. In this set of experiments, the recognition is done based on 7 EMG signals recorded from different muscles, and only one EMG signal is disturbed. The EMG signals from disturbed sensor and the user intent recognition results are illustrated in Fig. 2.

Plot A shows the EMG signal without disturbance. Plot G shows the ground truth: 1 means sitting and 2 means standing. Plot B shows the classification results of the UIR. Although there are a few errors, we see that the UIR works well when there is no disturbance.

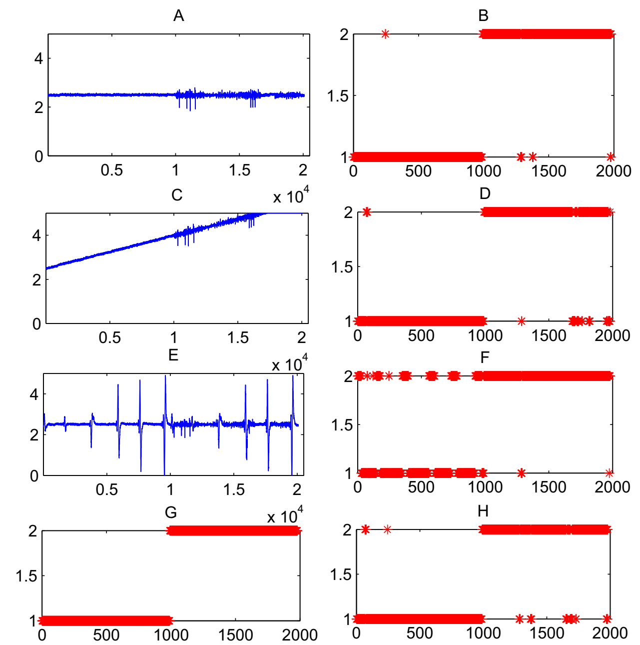

Fig. 2: Impact of Disturbances (A: normal EMG signal without disturbances; B: output of the UIR based on normal EMG signal; C: EMG signal contaminated by gradually changing baseline; D: output of the UIR based on EMG signal in C; E: EMG signal contaminated by motion artifacts; F: output of the UIR based on EMG signal in E; G: ground truth of user intent; H: output of the UIR with contaminated EMG sensor removed. In A, C, E, the x-axis is EMG sample index, and the y-axis is EMG amplitude. In B, D, F, G, H, the x-axis is sliding window index, and the y-axis represents user intent, where 1 means sitting and 2 means standing.)

Plot C and plot E show the EMG signals with motion artifacts and gradually increasing baseline shift, respectively. Plot D shows the classification results when motion artifacts are present. We see that the number of errors in the UIR significantly increases. Plot E shows the classification results when the baseline shift exists. When the baseline shift is large and cause signal saturation, the error number significantly increases. Therefore, it is important to detect the baseline shifts before it causes signal saturation.

Using the proposed detector, we can detect motion artifacts and baseline shifts. After removing the readings from the disturbed sensors, the UIR classification results are shown in Plot H. We can see that the classification error rate is greatly reduced, compared to the case with disturbance, but is still higher than the case without disturbance (plot B). This is because removing a sensor reduces the amount of information available to the UIR.

B. Demonstration of Disturbance Detection

From previous sections, we see that fast and accurate detection of these disturbances is important. In Fig. 3, we

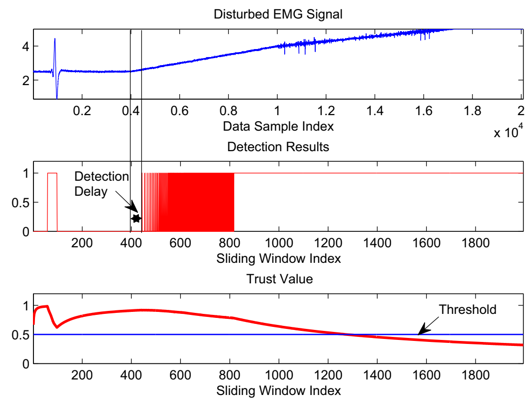

Fig. 3: Demonstration of CUSUM Detection Results

		Motion Artifacts	Baseline
DR		0.9960	1
FAR		0	0
DD	DD^{ini}	0.0198	23.4286
	DD^{ini}_{per}	0.039%	2.38%

TABLE I: Performance of abnormality detection for baseline noise and motion artifacts

demonstrate the operations of the proposed detector and trust calculation.

The upper plot shows the EMG signal that first experiences motion artifact and then gradually increasing baseline shift. The middle plot is the output of our detector: 1 means disturbance and 0 means no disturbance. The lower plot shows the trust value for this disturbed sensor.

We can observe that (1) the proposed detector can detect both baseline shift and motion artifacts, and (2) the detection delay for motion artifact is almost negligible, whereas the detection delay for the baseline shift is only about 40 windows (i.e. 400 samples with 1 KHz sampling rate) which is long before the signal saturation occurs. Additionally, the trust value drops for occasional motion artifact and then slowly recovers. In the time between window 440 and 800, detector is triggered by baseline shifts again and again, which leads to continuous drops of trust.

C. Detection Results

We have conducted 6 trials of sitting/standing tests, each of which has 7 EMG channels. For each EMG signal, we added 6 recorded motion artifacts (with $a = 1$) and one gradually baseline shift (with $b = 1.6 * 10^{-4}$). Thus, we have 252 motion artifact disturbed EMG signals and 42 signals with baseline shifts.

Table 1 shows the detection rate (DR), false alarm rate (FA), detection delay in terms of the number of windows (DD^{ini}), and detection delay divided by the duration of the disturbance (DD^{ini}_{per}), for the proposed detector. We make the following observations. (1) The proposed detector does not generate false alarms in all tests, and yields very high detection rate. (2) It responds to the motion artifact, which is sudden disturbance, quickly. The detection delay is only 0.0198 window, i.e. 0.2 data samples, on average. (3) It takes about 23.4 windows (i.e. 234 data samples) to detect the baseline shift, which is long before the signal saturation occurs.

V. CONCLUSION

A trust sensor interface (TSI) was designed to handle diverse disturbances originated in uncertain environment, which may distort EMG signals, cause errors in the UIR, and threaten the safety of amputees. Unlike other existing methods for handling disturbances, the TSI detects the presence of disturbances, evaluates EMG sensor reliability based on its "disturbance history", and provides trust report to the UIR. Preliminary experiments were conducted on an able-bodied human subject to demonstrate the proposed TSI when he was performing sitting and standing. The result shows the accurate and fast detection of disturbances. Additionally, the dynamic trust calculation is also demonstrated. The design of the TSI addresses the disturbance issue from a new angle and demonstrates a great potential in improving the reliability of the UIR. Our future work includes the trust evaluation of the output of the UIR and test of the TSI on amputees.

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