EMG Onset Detection
Comparison of Different Methods for a Movement Prediction Task based on EMG

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Abstract: In this work a study with 8 male subjects was conducted to compare three preprocessing methods for online capable movement prediction based on the recorded electromyogramm (EMG) signals of the right upper limb. One of the compared methods is the widely used Teager Kaiser Energy Operator (TKEO), the other two are a recently proposed method that is based on variance calculation of the signal and the standard deviation. Scope of the work was to show that fast methods, which are required for online processing, have at least the same performance as more classical approaches with higher demands on computational resources like the TKEO. An adaptive threshold was used for onset detection after preprocessing in all compared cases. Comparisons of preprocessing methods were done with respect to the performance in movement prediction and earliness of onset detection. The influence of different movement speeds on the prediction time and the performance were investigated as well. Results presented here show significant differences between the investigated preprocessing methods concerning the prediction time. As a further result of this study it could be shown that different movement speeds also have a significant effect on the prediction time.

1 INTRODUCTION

Motivated by a robotic application developed by our group that enables movement assistance by an exoskeleton, we were reviewing fast methods for movement prediction based on psychophysiological data. In previous studies we could show that the control of an exoskeleton benefits from prediction of movements based on psychophysiological data. It could be shown that the electroencephalogram (EEG) can be used to improve the interaction between human and an exoskeleton (Folgheraiter et al., 2012). However, due to the so called electromechanical delay between measurable changes in the electromyogramm (EMG) and the production of force in the corresponding muscle (Cavanagh and Komi, 1979) (Zhou et al., 1995) a fast detection of EMG onset activity can also be used to predict a physical movement. There are several studies concerning the automatic onset detection in the EMG. It is stated that preprocessing of EMG signals with the Teager Kaiser Energy operator (TKEO) improves the onset detection in comparison to simply filter the EMG data (Kaiser, 1990) (Li et al., 2007) (Solnik et al., 2010). However, fast and simple methods that require low computational resources are required for embedded signal processing that allow onboard analysis. Recently a preprocessing method that is based on the variance (VAR) calculation of EMG signals was proposed (Nikolic and Krarup, 2011), but to our knowledge so far no comparison of the TKEO and variance was done. Thus the comparison will be one goal of this paper.

After preprocessing onset detection can be performed with different threshold methods, like single threshold (Hodges and Bui, 1996) or multi threshold (Bonato et al., 1998) detection. The drawback of those methods is that the performance strongly depends on the threshold that is chosen once for the whole dataset. Recently an adaptive threshold method was proposed, in which the threshold is continuously updated based on the mean and standard deviation of a sliding window containing the recent data point and N previous data points (Semmaoui et al., 2012). Thus, onset detection can be adapted to possible changes in the EMG as they may occur during extensive behavior due to fatigue of the muscle. To our knowledge, this adaptive approach was not yet combined with the above mentioned preprocessing methods for the purpose of EMG onset detection. Therefore, another goal of this paper is to investigate the performance of the

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adaptive threshold in combination with the preprocessing methods.

To compare these different processing methods we did not only choose performance in detection but also the earliness of detection of EMG activity as a performance measure. In this context we also investigated different speeds of movements. Since different speeds of behavior do occur under natural condition, in which embedded systems for movement prediction might be applied and may influence predictability.

2 MATERIALS AND METHODS

2.1 Experimental Setup

Eight healthy right-handed male subjects (age 29.9 ± 3.3 years) participated in the study. The subjects were seated in a comfortable chair in front of a table. A monitor and two switches, a flat board and a buzzer, were located on the table. The flat board consisted of a plastic cuboid ($10 \times 10 \times 1.5$ cm) and a plastic plate ($10 \times 10 \times 0.4$ cm). The two parts were connected with a rotary joint. Inside the cuboid a microswitch and a spring were mounted. When putting a hand on the whole device, the plate will press the microswitch. By lifting the hand again the spring will push the plate up for approximately 0.5 cm which causes the switch to be released again. During the experiments both input devices were used to determine the begin or the end of a movement.

The experiments consisted of intention based movements of the right arm. The subjects were asked to perform 40 voluntary movements starting from the flat board to the buzzer and back. The events from the input devices (pressing/releasing) were marked in the recorded EMG data. Experiments with normal, slow, and fast speeds were performed. For each movement speed three runs were recorded.

Normal movements can be defined as natural ones. We simply ask the subjects to hit the buzzer in their own speed. These runs were performed first and used to make the test persons familiar with the experiment and the whole setup. They were not used for analysis. For slow movements a minimum time of 1 s from the flat board to the buzzer had to be satisfied. For fast movements the subjects were asked to move as fast as possible.

Since maximum movement speed differs between subjects, a preliminary investigation was done. Each subject was asked to perform the movement to the buzzer and back starting from the flat board, for 10 times as fast as possible. From the 10 movements the mean time needed to move from the flat board to the buzzer was calculated for each test person. Those average times plus an offset of 10 ms were used as the maximum time for fast movements. The maximum times varried from 120 to 275 ms. The experiments were designed and executed using Presentation (Neurobehavioral Systems, Inc.).

During the experiments a green circle with a black fixation cross was shown on the monitor. A resting time of 5 s between two movements had to be maintained. A wrong movement was indicated to the subject by changing the color of the circle from green to red for 100 ms. Wrong movements were defined as moving before the resting time (5 s) was expired, moving too fast, e.g., in case slow movements were requested, and moving too slow, e.g., in case fast movements were requested. Wrong movements were not taken into account for data analysis. In order to get the same amount of movements from each test person, a run was finished after 40 valid movements. To determine the physical begin of a movement a motion tracking system was used to track the position of the right hand, which is further explained in Section 2.3.1.

2.2 Data Acquisition

EMG was acquired at 5 kHz with a bipolar setup on four muscles of the right arm, named M. brachioradilis, M. bizeps brachii, M. triceps brachii, and M. deltoideus. For the measurement Ag/AgCl gel electrodes were used. The skin of the test persons was prepared with medical alcohol to obtain better conductivity. The signals were amplified and digitalized by a BrainExG MR (Brain Products GmbH, Germany) amplifier and saved to a computer. The events from the two switches, meaning pressing and releasing, were marked in the EMG data. The motion tracking system consisted of three ProReflex1000 cameras (Qualisys AB, Sweeden) and a passive infrared marker mounted on the back of the right hand of the subjects. The position of the marker was tracked with a frequency of 500 Hz and stored on a computer. The accuracy of the system was approximately 0.15 mm.

2.3 Data Processing

2.3.1 Finding Physical Movement Onsets

The motion tracking system was used to determine the physical movement onset. For this the movement speed of the right hand was derived from the tracking data. Afterwards, the EMG and the tracking data were synchronized. As mentioned before in Subsection 2.1, the begin of a movement was marked in the

EMG data using a flat board. Since the device contains a microswitch, it is obvious that the subject was already moving when the switch is released. However, after synchronizing the EMG data and the movement speed, the markers from the flat board were used as a starting point for finding the physical movement onsets in the tracking data. Starting from those marker positions the movement speed was analyzed backwards. Once the movement speed was below a threshold, the detected position was saved as the physical movement onset. This threshold was set to 0.15 mm/sample, since this is the given accuracy of the tracking system. This was done consecutively for all recorded runs and contained movements. Figure 1 illustrates the procedure. The vertical dashed line indicates the position of the marker from the flat board and the solid vertical line indicates the found position of the physical movement onset.

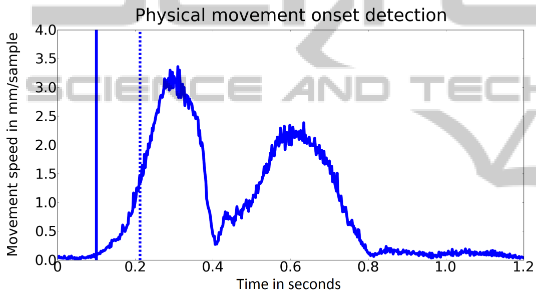


Figure 1: Physical movement onset detection. The movement speed is show. The dashed vertical line indicates the position of the marker from the flat board and the solid one the detected physical movement onset.

In the further analyses the determined physical movement onsets, found with the motion tracking system, were used as the reference for the onset detection in the EMG data.

2.3.2 Preprocessing of EMG Data

Three different methods Teager Kaiser Energy operator (TKEO), variance, and standard deviation were used to preprocess the EMG data. The goal of preprocessing is to enhance the signal-to-noise ratio of the signals. The TKEO is widely used as a preprocessing method in EMG onset detection. The algorithm calculates the energy of the signal in a very efficient way. Only three consecutive samples are needed. The formula for the TKEO is given as:

$$\Psi(t) = x(t)^2 - (x(t-1)x(t+1)) \tag{1}$$

where $x(t)$ is the current EMG sample.
As one can see, one of the required samples lays in the future. In order to use the TKEO online, the formula is thus redefined as:

$$\Psi'(t) = x(t-1)^2 - (x(t-2)x(t)). \tag{2}$$

Before applying the TKEO, the data is filtered using a 20 Hz second order butterworth high-pass filter. The filtering is done to remove motion artifacts, like movement of cables or changes in resistance at the electrodes. Afterwards the energy of the EMG signal is calculated using the TKEO. At the end the resulting energy is smoothed to remove large fluctuations.

The variance method for preprocessing EMG signals is based on the following equation (Nikolic and Krarup, 2011):

$$v(t) = \frac{1}{N-1}\sum_{i=-m}^{m} x^2(t+i) - \left(\frac{1}{N-1}\sum_{i=-m}^{m} x(t+i)\right)^2 \tag{3}$$

where $N = 2m+1$ is the window length.
Here again samples do lay in the future, therefore the formula is reformulated as follows for an online use of the variance:

$$v(t)' = \frac{1}{N-1}\sum_{i=-2m}^{0} x^2(t+i) - \left(\frac{1}{N-1}\sum_{i=-2m}^{0} x(t+i)\right)^2 \tag{4}$$

When using the variance for preprocessing, a moving window of fixed length is used. The variance of the window is assigned to the last data point. This is done consecutively for all samples of the data, resulting in a signal with smoothed baseline noise and enhanced amplitudes during movement phases. The sensitivity of this method can be adjusted by varying the length of the window. For smaller windows the method reacts faster to changes. The drawback is that artifacts are also more amplified. Thus by increasing the window size the baseline noise gets smoother but the amplitudes during movement phases are less amplified.

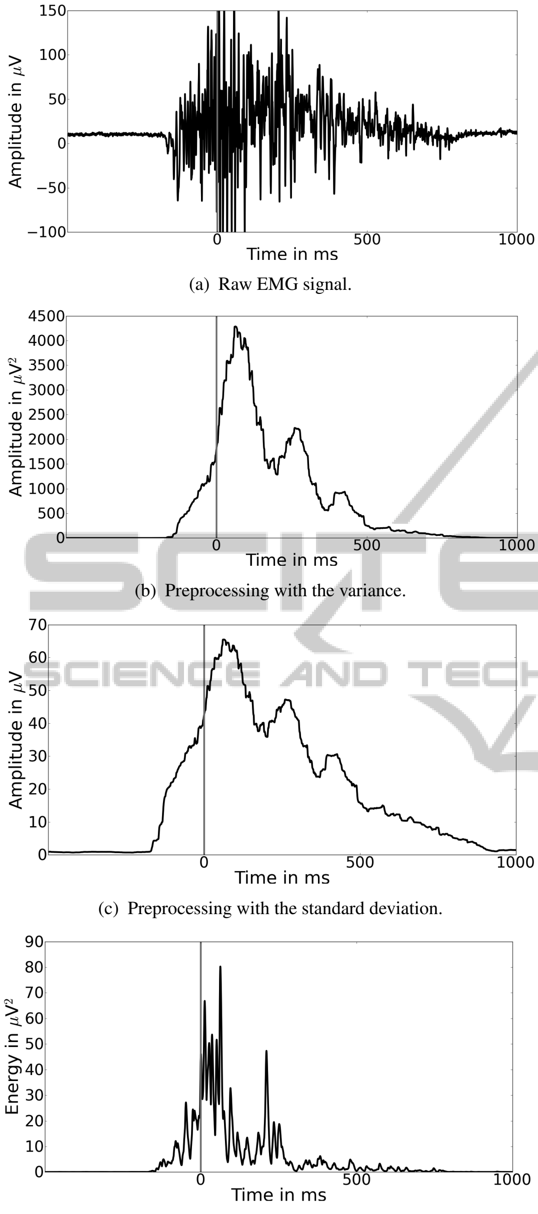
The procedure for the standard deviation is the same as for the variance. Even if the calculations of both methods are very similar, they have different mathematical properties.

For later analysis the total computational time for all preprocessing methods was measured. A comparison of all methods is shown in Figure 2.

2.3.3 Onset Detection

For onset detection in the preprocessed EMG data an adaptive threshold approach was used. The formula is given as:

$$T(t) = \bar{x}(t)_N + p\mu(t)_N \tag{5}$$



(a) Raw EMG signal.

(b) Preprocessing with the variance.

(c) Preprocessing with the standard deviation.

(d) Preprocessing with the TKEO.

Figure 2: Resulting signals after the application of preprocessing methods: a) original EMG signal, b) after variance, c) after standard deviation, and d) after TKEO.

with $\bar{x}$ the mean value, μ the standard deviation, N the length of the window for the mean and standard deviation and p the sensitivity factor of the threshold (Semmaoui et al., 2012). The preprocessed data was passed to the adaptive threshold procedure using various values for the parameters of the different methods. For the standard deviation and variance window sizes of $100, 250$, and 500 samples were used. For the threshold the windows of sizes $5000, 10000, 15000$, and 20000 samples and p values of $0-19$ were used. As performance measures for preprocessing methods balanced accuracy and prediction time were used.

Balanced Accuracy. The balanced accuracy metrics is calculated as the mean of sensitivity and specificity (Velez et al., 2007). The metrics is defined as:
$Balanced\_accuracy \stackrel{\text{def}}{=} 0.5 * [\frac{TP}{TP+FN} + \frac{TN}{TN+FP}]$
where TP, TN, FP and FN represent the number of true positives, true negatives, false positives and false negatives, respectively. A classification was counted as TP, if the signal exceeded the threshold in range $500-0$ ms before a physical movement, classifications in other ranges were counted as FP. Not detecting a movement was counted as FN. The number of TN was counted as the amount of periods between two movements where no FP's occurred. For the onset detection, parts of the data containing wrong movements were not taken into account. Therefore the whole wrong movement plus ranges of 1 s before and after it were rejected from the signal.

Prediction Time. The prediction time is defined as the elapsed time between the detected onset in the EMG signal and the physical movement onsets detected by the motion tracking system.

For all combinations of the above mentioned parameters the balanced accuracy and prediction time for all recorded runs were calculated. Afterwards, a cross validation over all subjects was done. Thus, the mean balanced accuracy and prediction time for seven out of the eight subjects were calculated. From those results the best combination of parameters, meaning those which produce the highest balanced accuracy with earliest prediction time, was chosen and tested on the data from the remaining subject. This was done separately for all preprocessing methods and subjects. The mean trainings results for different EMG channels are shown in Table 2. The training showed that best results could be obtained when using signals from the M. bizeps brachii. Results were statistically analyzed by repeated measures ANOVA with *method (VAR, STD, and TKEO)* and *speed (slow and fast)* as within-subjects factor.

3 RESULTS

Results of all described analysis are summarized in Table 1. Statistical analysis showed that there are significant differences between the three compared preprocessing methods for the prediction time, but not for the balanced accuracy. STD has significantly earlier prediction times compared to the two other meth-

Table 1: Results of all preprocessing methods on the dataset from 8 subjects with slow and fast movement speeds. PT, and BA indicate prediction time in ms and balanced accuracy respectively.

	VAR				STD				TKEO			
	slow		fast		slow		fast		slow		fast	
SUB	PT	BA	PT	BA	PT	BA	PT	BA	PT	BA	PT	BA
1	202	0.86	52	0.85	216	0.88	65	0.84	195	0.88	50	0.81
	214	0.88	54	0.88	230	0.88	66	0.88	196	0.86	50	0.9
	209	0.88	50	0.96	222	0.9	64	0.94	191	0.89	49	0.93
2	194	0.81	33	0.91	215	0.84	39	0.91	201	0.8	36	0.9
	221	0.92	50	0.78	226	0.9	50	0.63	207	0.95	57	0.65
	175	0.74	44	0.9	182	0.74	57	0.9	143	0.81	42	0.81
3	184	0.8	91	0.58	190	0.8	101	0.56	176	0.8	86	0.63
	175	0.88	63	0.63	182	0.88	78	0.63	167	0.83	55	0.63
	177	0.78	54	0.51	178	0.73	76	0.49	169	0.81	29	0.41
4	129	0.4	46	0.86	115	0.41	47	0.81	119	0.4	38	0.79
	93	0.4	31	0.66	102	0.44	31	0.69	110	0.44	31	0.71
	106	0.46	33	0.66	135	0.45	47	0.64	99	0.44	37	0.6
5	198	0.95	43	1.0	245	0.95	47	1.0	184	0.9	41	0.96
	216	0.9	56	1.0	244	0.93	65	1.0	197	0.88	40	0.94
	186	0.9	46	0.98	218	0.9	50	0.98	189	0.91	46	0.96
6	173	0.89	49	0.91	219	0.93	70	0.91	163	0.93	46	0.88
	149	0.86	46	0.91	177	0.84	53	0.91	139	0.91	42	0.93
	182	0.85	38	0.83	213	0.85	73	0.84	148	0.89	28	0.88
7	73	0.86	44	0.96	81	0.9	45	0.96	84	0.73	44	0.94
	75	0.73	42	0.96	86	0.63	43	0.89	70	0.58	41	0.93
	47	0.44	26	0.84	59	0.48	29	0.81	47	0.45	27	0.86
8	218	0.76	57	0.96	238	0.76	76	0.96	207	0.8	56	0.96
	234	0.79	49	0.88	252	0.79	66	0.85	203	0.8	49	0.83
	282	0.88	52	0.98	296	0.86	58	0.98	248	0.94	46	0.98

Table 2: Mean balanced accuracy for training with different EMG channels, with all, EMG1, EMG2, EMG3, and EMG4 representing mean of all channels, M. brachioradialis, M. bizeps brachii, M triceps brachii, and M. deltoideus respectively.

	VAR	STD	TKEO
all	0.79	0.78	0.75
EMG1	0.66	0.65	0.62
EMG2	0.81	0.81	0.8
EMG3	0.63	0.62	0.6
EMG4	0.68	0.69	0.66

ods. [prediction time: $F(2,46) = 46.4$, $p < 0.001$, pairwise comparisons: VAR vs. STD = 0.001, VAR vs. TKEO = n.s., STD vs. TKEO = 0.001; balanced accuracy: $F(2,46) = 2.59$, $p = n.s.$, all each pairwise comparisons: $p = n.s.$]

The same pattern was found for different movement speeds. Significant differences for the prediction time, but not for the accuracy were found. Slow movements lead to an earlier prediction time. [prediction time: $F(1,23) = 142.1$, $p < 0.001$, all each pairwise comparisons: $p < 0.001$; balanced accuracy: $F(1,23) = 1.57$, $p = n.s.$, all each pairwise comparisons: $p = n.s.$].

It was found that the calculation time for the TKEO needs approximately 1.5 times the time the other two methods need.

The following parameters were determined for the preprocessing methods in the training phase. VAR windows size (WS) of 100 samples with $p = 10$ and 20000 WS for the adaptive threshold, STD WS of 100 samples with $p = 7$ (subjects 1,3,5,6,8) and $p = 8$ (subjects 2,4,7) and 20000 WS for the adaptive threshold, and for the TKEO $p = 7$ and 20000 WS for the adapt. threshold.

4 DISCUSSION AND CONCLUSIONS

Since the calculation time for the VAR and STD is 1.5 times faster compared to the time needed by the TKEO, they suite better the needs for online processing of EMG data with embedded systems. Although, the STD prediction time in average is 13 ms earlier compared to the prediction time of VAR, one may prefer VAR for embedded systems, since the calculation of the square root for the STD is computational very expensive on such devices. However, the decision depends on the application, if the earliness is very important, one would use STD for preprocessing. Further, by combining VAR or STD with the adaptive threshold very good results for movement prediction could be achieved. In summary, a simple and computational very efficient way of predicting movements using EMG data can thus be realized.

For some subjects rather large variations in prediction times, especially for slow movements, could be observed. Mainly two reasons could have led to these results. First, it is possible that the subjects somehow pretensioned there muscles, even if they were told to move right away without any preparation. This could have led to an earlier movement prediction. Hence, if the subjects did so for some movements and for other not, this could explain the variation in prediction times. Second, the only constraint for slow movements was a minimum time of 1 s for the movement from the flat board to the buzzer Section 2.1. The subjects were asked to perform the movements with a steady speed. However, the subjects may have varied the initial movement speed, e.g., fast start followed by a slower movement. Movements with fast initial speed may be detected later compared to those with slow initial speed. Thus, the differences in prediction time could be explained by the variation of initial movement speeds.

Our results show that it is possible to predict both slow as well as fast movements. We found that for slow movements earlier prediction times were achieved. Whether this is a real effect, or might be due to experimental setup, i.e., datasets from slow and fast movements were merged for training, cannot finally answered here. Due to our focus on a real application, parameters were not optimized for a certain speed of movement. This was done since in applications one cannot relay on a certain movement speed and the methods will have to deal with both, fast and slow movements.

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REFERENCES

Bonato, P., D'Alessio, T., and Knaflitz, M. (1998). A statistical method for the measurement of muscle activation intervals from surface myoelectric signal during gait. *IEEE Transactions on Biomedical Engineering*, 45(3):287–299.

Cavanagh, P. R. and Komi, P. V. (1979). Electromechanical delay in human skeletal muscle under concentric and eccentric contractions. *European Journal of Applied Physiology and Occupational Physiology*, 42(3):159–163.

Folgheraiter, M., Jordan, M., Straube, S., Seeland, A., Kim, S.-K., and Kirchner, E. A. (2012). Measuring the improvement of the interaction comfort of a wearable exoskeleton. *International Journal of Social Robotics*, 4(3):285–302.

Hodges, P. W. and Bui, B. H. (1996). A comparison of computer-based methods for the determination of onset of muscle contraction using electromyography. *Electroencephalography and Clinical Neurophysiology*, 101(6):511–519.

Kaiser, J. F. (1990). On a simple algorithm to calculate the 'energy' of a signal. In *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing ICASSP-90. Conf*, pages 381–384.

Li, X., Zhou, P., and Aruin, A. S. (2007). Teager-kaiser energy operation of surface EMG improves muscle activity onset detection. *Annals of Biomedical Engineering*, 35(9):1532–1538.

Nikolic, M. and Krarup, C. (2011). EMGTools, an adaptive and versatile tool for detailed EMG analysis. *Biomedical Engineering, IEEE Transactions on*, 58(10):2707 –2718.

Semmaoui, H., Drolet, J., Lakhssassi, A., and Sawan, M. (2012). Setting adaptive spike detection threshold for smoothed TEO based on robust statistics theory. *IEEE Transactions on Biomedical Engineering*, 59(2):474 – 482.

Solnik, S., Rider, P., Steinweg, K., DeVita, P., and Hortobgyi, T. (2010). Teager-kaiser energy operator signal conditioning improves EMG onset detection. *European Journal of Applied Physiology*, 110(3):489–498.

Velez, D. R., White, B. C., Motsinger, A. A., Bush, W. S., Ritchie, M. D., Williams, S. M., and Moore, J. H. (2007). A balanced accuracy function for epistasis modeling in imbalanced datasets using multifactor dimensionality reduction. *Genetic Epidemiology*, 31(4):306–315.

Zhou, S., Lawson, D. L., Morrison, W. E., and Fairweather, I. (1995). Electromechanical delay in isometric muscle contractions evoked by voluntary, reflex and electrical stimulation. *European Journal of Applied Physiology and Occupational Physiology*, 70(2):138–145.