Detection of Onset and Offset Time of Muscle Activity in Surface EMG using the Kalman Smoother

Jung Hoon Lee[1], Hyun Sook Lee[2], Young Hee Lee[3], Young Ro Yoon[1]

[1]*Department of Biomedical Engineering, Graduate School of Yonsei University, Wonju, Republic of Korea*
[2]*Department of Oriental Biomedical Engineering, Sangji University, Wonju, Republic of Korea*
[3]*Department of Rehabilitation Medicine, Yonsei University Wonju College of Medicine, Wonju, Republic of Korea*
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Abstract

A visual decision by clinical experts like physical therapists is a best way to detect onset and offset time of muscle activation. The current computer-based algorithms are being researched toward similar results of clinical experts. The new algorithm in this paper has an ability to extract a trend from noisy input data. Kalman smoother is used to recognize the trend to be revealed from disorderly signals. Histogram of smoothed signals by Kalman smoother has a clear boundary to separate muscle contractions from relaxations.

To verify that the Kalman smoother algorithm is reliable way to detect onset and offset time of muscle contractions, the algorithm of Robert P. Di Fabio (published in 1987) is compared with Kalman smoother. For 31 templates of subjects, an average and a standard deviation are compared. The average of errors between Di Fabio's algorithm and experts is 109 milliseconds in onset detection and 142 milliseconds in offset detection. But the average between Kalman smoother and experts is 90 and 137 milliseconds in each case. Moreover, the standard deviations of errors are 133 (onset) and 210 (offset) milliseconds in Di Fabio's one, but 48 (onset) and 55 (offset) milliseconds in Kalman smoother. As a result, the Kalman smoother is much closer to determinations of clinical experts and more reliable than Di Fabio's one.

Key words : onset, offset, EMG, Kalman smoother

I. INTRODUCTION

The surface electromyography (EMG) signal is widely used as a suitable means to analyze the physiological processes involved in producing joint movements.[1] Surface EMG is very convenient trigger source in muscle-machine interface, because it is more simple to record than the needle-electrode EMG. Applications of surface EMG can be useful in order to control rehabilitation devices or to study the biomechanics and motor control of the musculo-skeletal system during different movements of the legs and arms.[2]

Onset and offset (termination) time of muscle activations are a key variables in a research of surface EMG. A best way to detect onset and offset time of muscle activation is a visual decision of clinical experts like physical therapists. Because of this, a purpose of computer-based algorithm is to detect onset and offset time exactly as like human perception.

In 1987, Richard P. Di Fabio developed the first computer-based algorithm to detect an onset time.[3] It was based on threshold multiplied by 1SD (1 × standard deviation), 2SD, or 3SD and duration of a single EMG pulse. After Di Fabio, some techniques have been researched to detect onset time or interval of muscle activation.[4,5,6,7,8] Most of the techniques commit an error when spike noise or white noise is mixed with signal. On the other hand, the human perception can recognize a trend of muscle activation neglecting noises. New technique must have this ability to be robust from noisy signals.

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Corresponding Author : Young-Ro Yoon
Medical Industry Techno Tower #201, Maeji, Heungup, Wonju, Kangwon, 220-842, Korea.
Tel : 82-33-760-2440 / Fax : 82-33-763-4050
E-mail : yoon@yonsei.ac.kr

II. BACKGROUNDS

A. Di Fabio's Algorithm

Di Fabio's algorithm is most commonly used to detect onset time and it is also a good reference to benchmark a new technique. Di Fabio used two variables; threshold and duration. The threshold is calculated by adding SD factors to a mean value of resting state of EMG signals. The SD factors mean standard deviation of resting stage by multiplying 1, 2, or 3. The duration is a period of one rectified pulse.

A pulse beyond the threshold is tested within its period, or not. The two conditions are selected experimentally as the conditions yield the best output. Figure 1 shows statistical approach to distinguish activation signal from baseline (resting

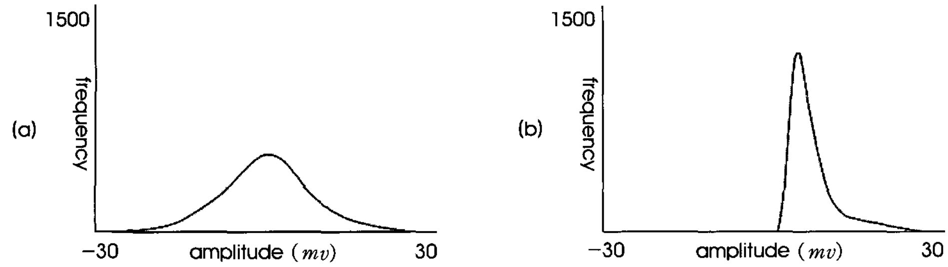

Fig. 1. Statistical background of Di Fabio's algorithm. (a) is non-rectified signal, and (b) is rectified signal. μ is a mean value of baseline signals, and σ is SD. Di Fabio uses baseline signal as a Gaussian-random signal. Di Fabio wants to distinguish two signals - activations and baselines - using statistical approach.

state) signal of Di Fabio's algorithm. We use this technique compared with the results of our new algorithm's results.

B. Problems in Existing Techniques

In existing techniques to detect onset or offset time of muscle activation, there are a lot of problems to yield some errors.[9][10] These problems are classified by domains; time and frequency. In time domain, the spike and white noise is difficult to be filtered out.[2] A type I noise is the similar kind of the spike noise, and a type II noise is the similar of the white noise. The type I and II noise is easy to be recorded simultaneously during recording EMG signals. Especially in Di Fabio's algorithm, the type I noise on the baseline state before muscle activation leads to early-detection or advanced -detection of onset time. Similarly, the type II noise on the whole state (both of the baseline and activation state) leads to delayed-detection of onset time. Figure 2 shows problems in time domain affected by the type I and II noise.

In frequency domain, the other problems have to be solved. Figure 3 represents ECG artifacts on EMG signals. The artifacts in this case share with some bandwidth of frequencies, because EMG signal has a wide bandwidth of its frequencies. The ECG artifacts can not be removed by frequency-based filter.

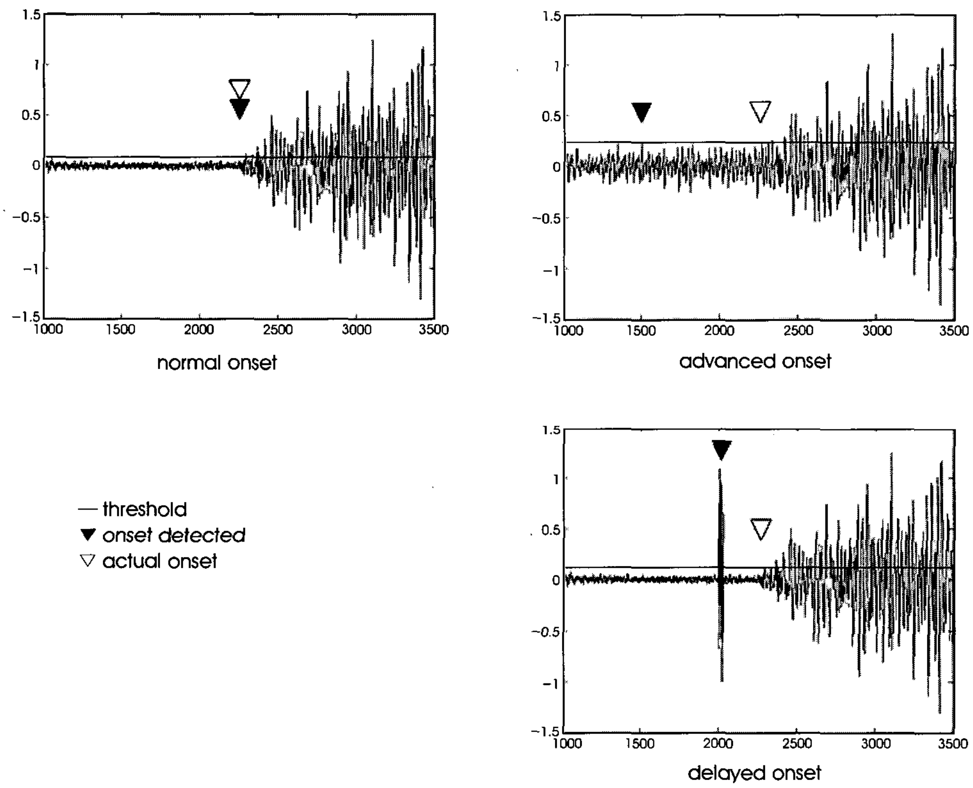

Fig. 2. Advanced or delayed detection of onset time caused by type I and II noise.

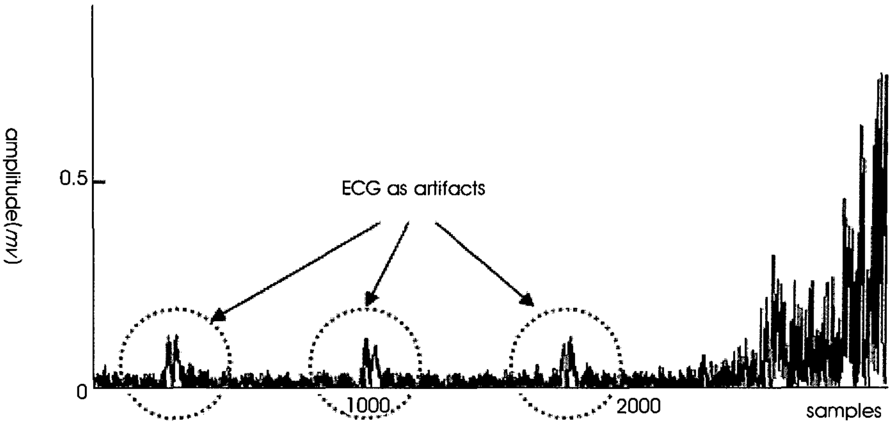

Fig. 3. ECG artifacts on EMG signals. ECG artifacts can not be filtered out by frequency domain filter.

In this paper, we argue that new algorithm must have an ability to recognize a big trend of EMG signals as like the perception of human. If the new algorithm has the ability to extract a trend of muscle activation, some noises in time and frequency domain are not a problem to detect onset time in the exactly same process of recognition a trend by clinical experts. Because EMG signals are also the most random signals within biomedical signals, the new algorithm have to be used in random signal models.

C. Kalman Smoother

Kalman filter was made by Rudolf E. Kalman in 1960. The Kalman filter is a recursive estimator.[12][13] This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. Because of this sample-by-sample approach, The Kalman filter is very effective recursive computational solution. Figure 4 shows steps of Kalman filtering. These steps are calculated repeatedly in every sampling period.

To use the Kalman filter in EMG signal processing, Gauss-Markov process model is needed.[14] In this new model, EGRN (Envelope adding Gaussian Random Noise) model, we suppose that the EMG signal is summation of Gaussian-random noise and original signal which has clear

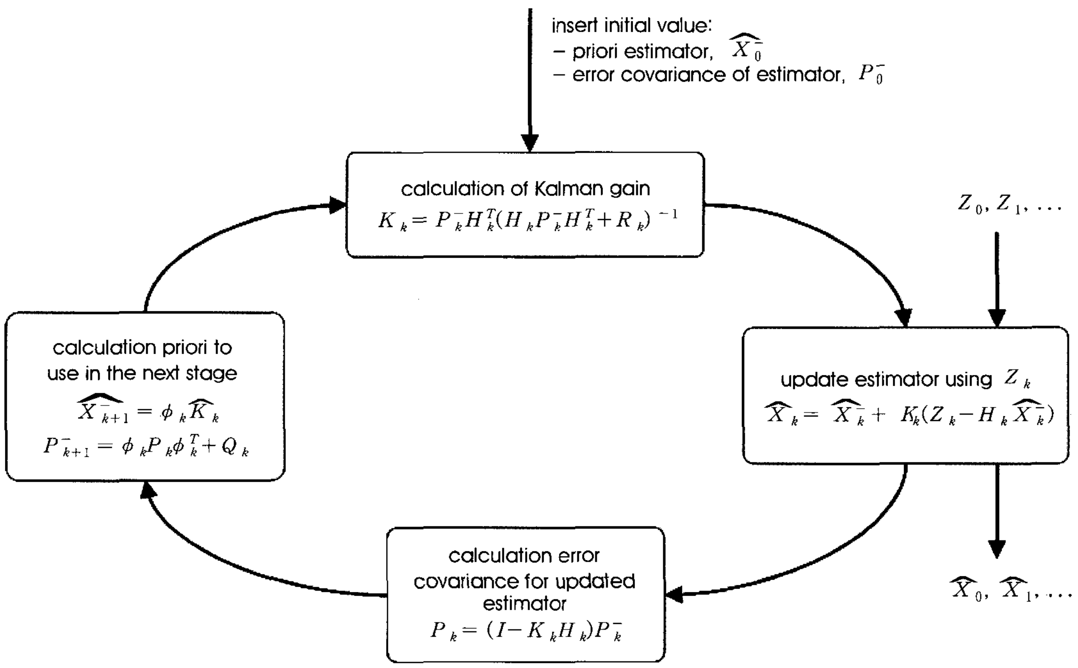

Fig. 4. Recursive update loop of the Kalman filtering.

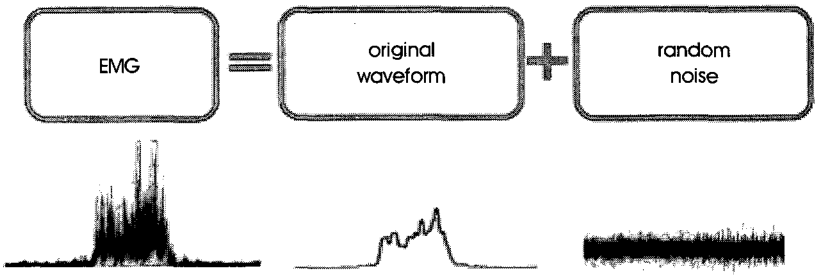

Fig. 5. The new model of EMG signals. EMG signals are summation of original waveform and Gaussian distributed random noise.

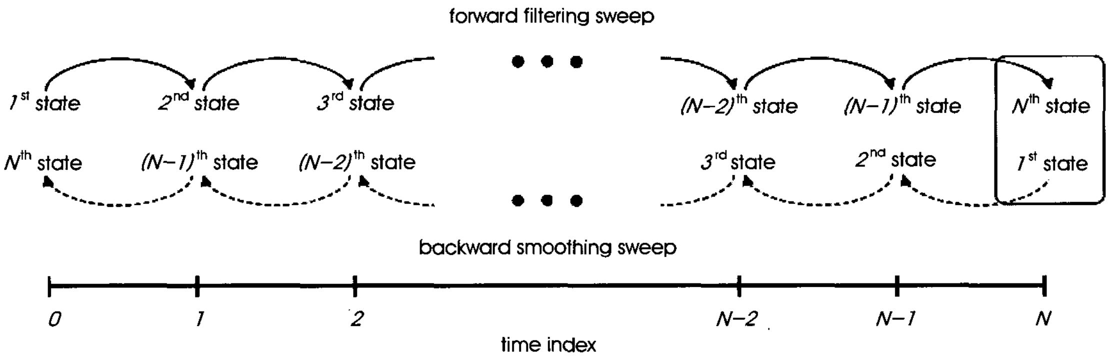

Fig. 6. Off-line process of the Kalman smoother. The forward filtering sweep means the Kalman filtering. The backward smoothing sweep is the off-line process which is performed after sampling and filtering.

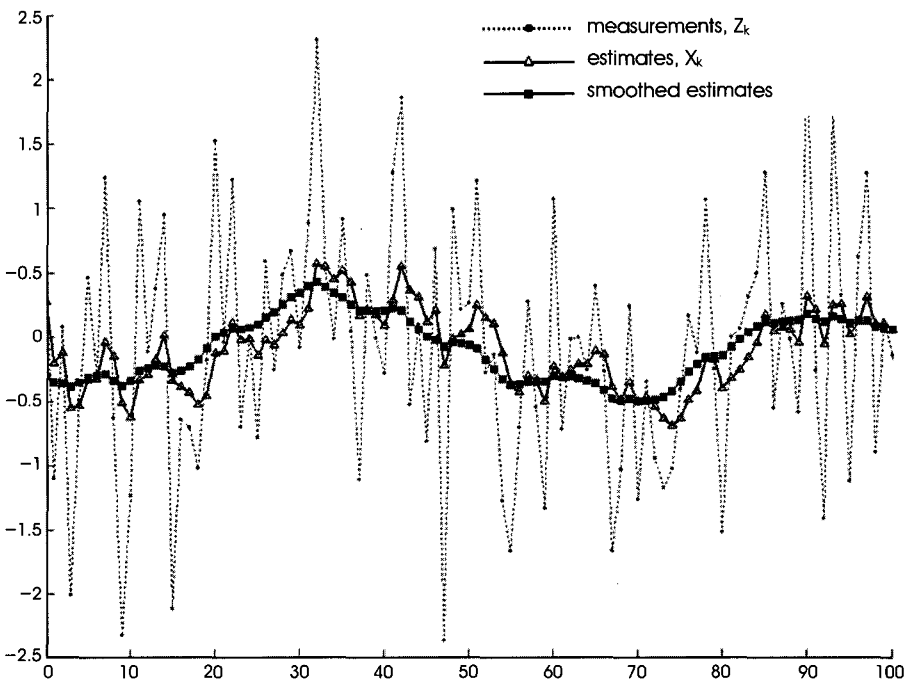

Fig. 7. The Kalman filter and smoother simulation for random signals - 100 samples.

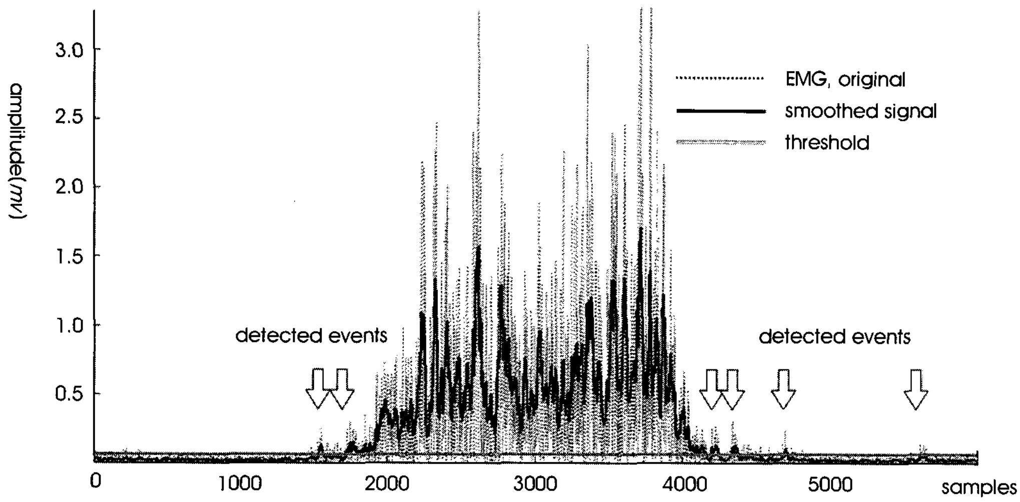

Fig. 8. Necessity of iterated Kalman smoother.

envelope waveform. This model is showed in Figure 5.

The Kalman smoother is prediction of backward sweep after Kalman filtering.[14] In figure 6, this process shows the results from the time index 0 to N. Figure 7 represents the Kalman filter and smoother simulation for random signals (100 samples). In figure 7, estimate X_k means the results of the Kalman filtering and the smoothed estimates signal means the results of the Kalman smoothing.

Ⅲ. METHODS

A. Evaluation of the Kalman Filter and Smoother

The Kalman filter is the recursive update process. The update process goes on with orders from equation (1) to (5) sequentially. Z_k is input sequence, K_k is the Kalman gain and P_k is the error covariance matrix. H_k is a vector shows a relationship between Z_k and X_k at the time t_k, ϕ_k is the state transform matrix represents a relationship between the state X_k and X_{k+1}. Q_k is the covariance matrix of the white sequence W_k and R_k is the covariance matrix of the other white sequence V_k.

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{1}$$

$$\hat{X}_k = \hat{X}_k^- + K_k (Z_k - H_k \hat{X}_k^-) \tag{2}$$

$$P_k = (I - K_k H_k) P_k^- \tag{3}$$

$$\hat{X}_{k+1}^- = \phi_k \hat{X}_k \tag{4}$$

$$P_{k+1}^- = \phi_k P_k \phi_k^T + Q_k \tag{5}$$

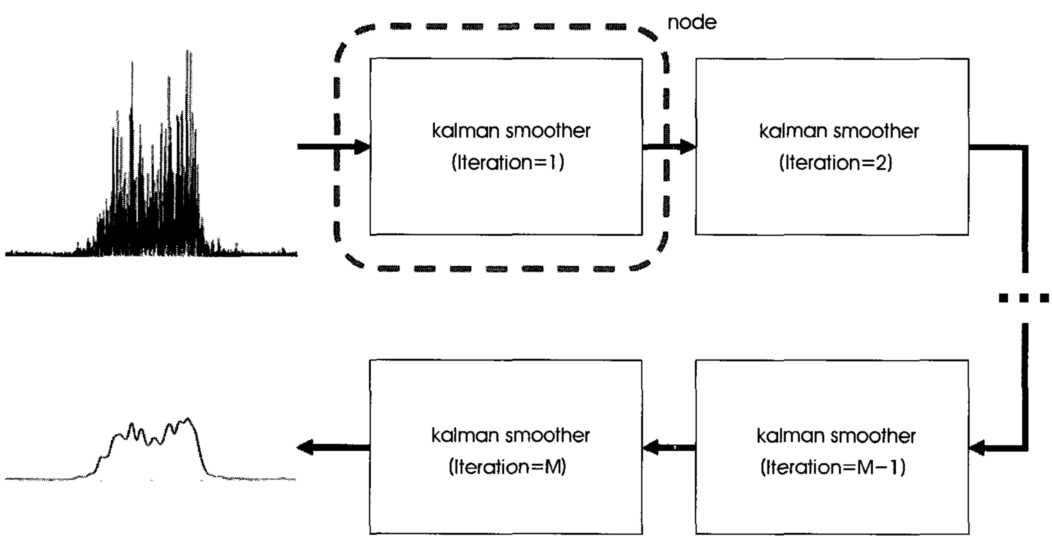

Fig. 9. Cascading of the Kalman smoother. EMG signal is getting more clear through iterated nodes.

The process of the Kalman smoother is composed of forward sweep and backward sweep. The forward sweep means the process of the Kalman filtering. In the forward sweep, some variables must be stored as they are used in the next (backward) sweep. Probabilistic information like priori and posteriori must be stored. And error covariance, P_k, also has to be stored. Using the stored variables, smoothing process can be started with the last output sample of the forward sweep as an initial value. Equation (6) represents the Kalman smoother process. $A(k)$ is smoothing gain which is defined as like equation (7). Both of forward process and backward process are sample-by-sample approaches.

$$\hat{X}(k|N) = \hat{X}(k|k) + A(k)[\hat{X}(k+1|N) - \hat{X}(k+1|k)] \tag{6}$$

$$A(k) = P(k|k)\phi^T(k+1, k)P^{-1}(k+1|k) \quad where \quad k = N-1, N-2, \cdots, 0 \tag{7}$$

B. Iterated Process

The Kalman smoother must be iterated sufficiently not to detect errors. Figure 8 shows some fault-detected events as onset or offset in a signal which is smoothed by the Kalman smoother just one time. Iterated process of smoothing makes

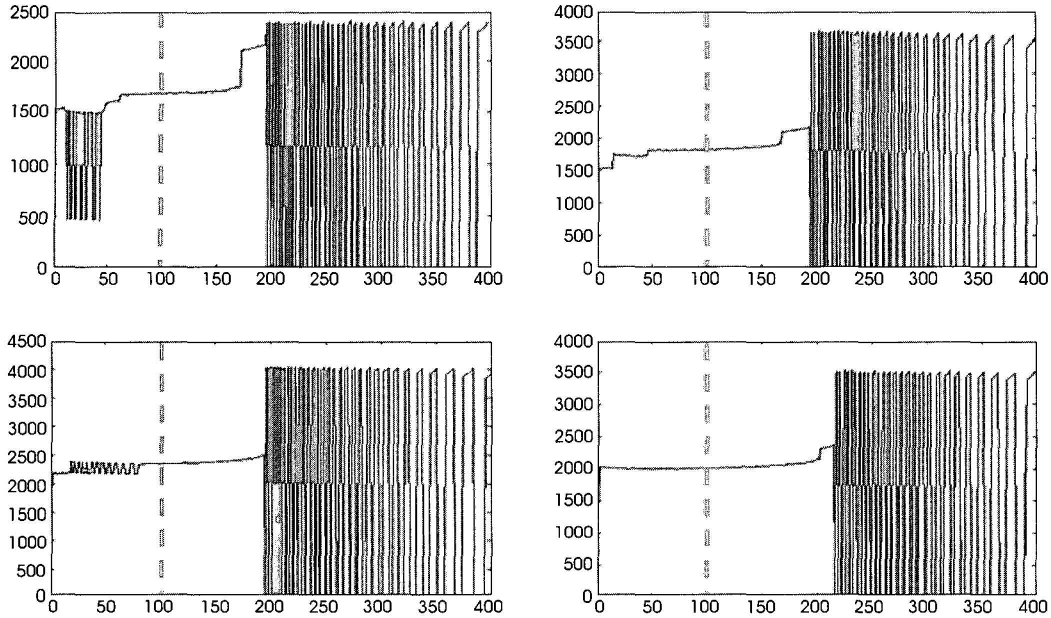

Fig. 10. Exhaustive search for stable number of iteration in the Kalman smoother. Observations of iterations are tested from 1 to 400. Sampling frequency is 1kHz.

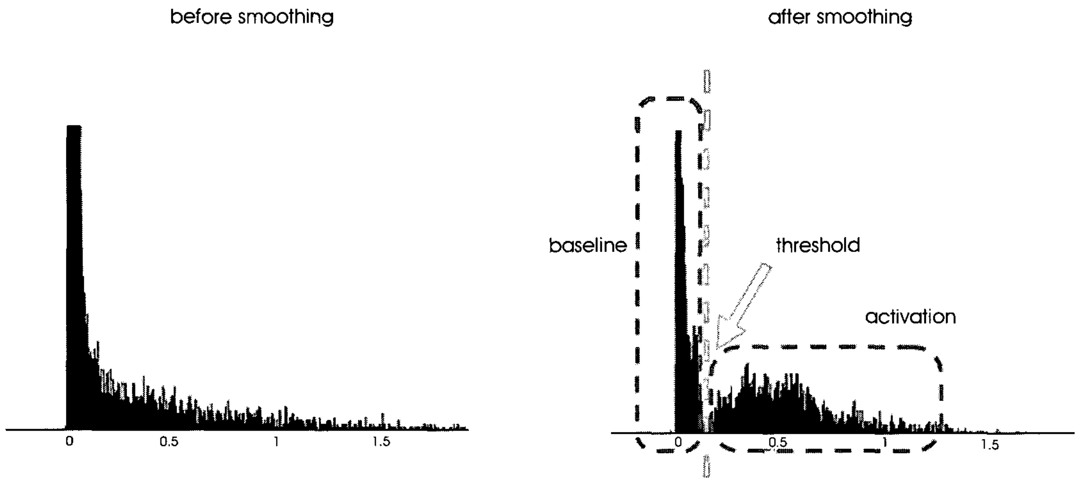

Fig. 11. Threshold detection using histogram. Baseline signals are changed to be separable from activation signals by the Kalman smoother.

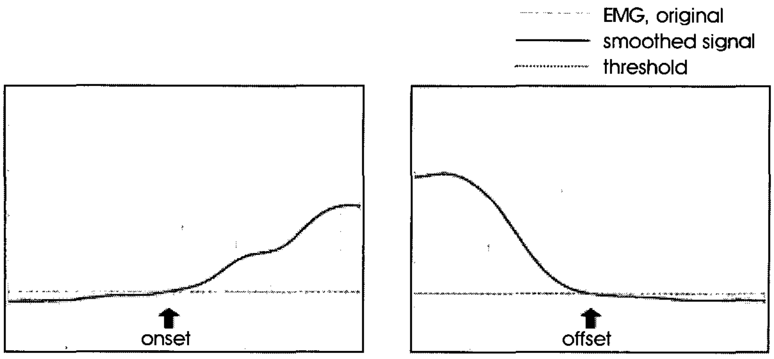

Fig. 12. Detection results of onset and offset time.

EMG signal clear to be understood intuitively as like in figure 9. To find an appropriate number of iterations, we tested whole data of individual subjects exhaustively. In figure 10, the examples of four subjects show some fluctuations of threshold with exhaustive searching. As a result, we can find intervals of numbers of iterations. Obviously, there is an optimal (or stable) number of iterations as a hundred (100).

C. Histogram of Iterated Signal after Smoothing

After repetitive smoothing process, the statistical characteristics of signal can be changed. The noisy EMG signal is very close to random signal. Histogram of non-smoothed signal is the Gaussian distribution. It is hard to distinguish the muscle activation from the baseline state.

However, the Kalman smoother make signal to be divided in two classes; baseline and activation. Figure 11 shows this effect of the Kalman smoother. Then, the threshold is determined to a valley of the histogram between baseline signals and activation signals.

D. Experimental Methodologies and Subjects

The EMG signals are recorded on the biceps brachii muscle using MP150 system which is produced by BioPac. Ground for differential amplification is located at wrist of the same arm. To minimize impedance of skin, the surface EMG electrodes are attached to the points of skin after cleaning up carefully. Dominant arm of subject is selected and fixed on table with height of his chest. Subjects lift and release his fixed arm repetitively and freely. The experiment is lasted for about 1 minute.

The subjects are 31 persons with no abnormalities in his arm or muscles of contraction. Their averaged age is 26.5 years old, and the standard deviation is 2.4 years old. All of the subjects are men who doesn't have any experiences of surgical treatments.[15] Before starting their experiments, they are fully understood what they do. To increase accuracy, preliminary experiments are performed at least more than one time.

Ⅳ. RESULTS

Figure 12 shows detection results of onset and offset time by the Kalman smoother algorithm. To verify the algorithm of the Kalman smoother, visual decision of two physical therapists are used as a reference. Di Fabio's method is compared with this algorithm as a control.

Di Fabio's method is combinations of two variables which are threshold and duration. The threshold means the standard deviation (SD) multiplied factor 1, 2 or 3. The duration is determined experimentally from 5㎳ to 25㎳ at 5㎳ intervals. 15 combinations can be made by 3 conditions from the thresholds and 5 conditions from the durations. Table 1 shows results at 2SD and 10㎳ condition. At this condition, Di Fabio's method can yield the minimum errors. Although it can yield the minimum errors, they are much bigger than errors in the Kalman smoother. In other words, the results in the

Table 1. Results in 2SD, 10㎳ condition.

	Di Fabio error		Kalman smoother error	
	onset (ms)	offset (ms)	onset (ms)	offset (ms)
mean	109	142	90	137
standard deviation	133	210	48	55

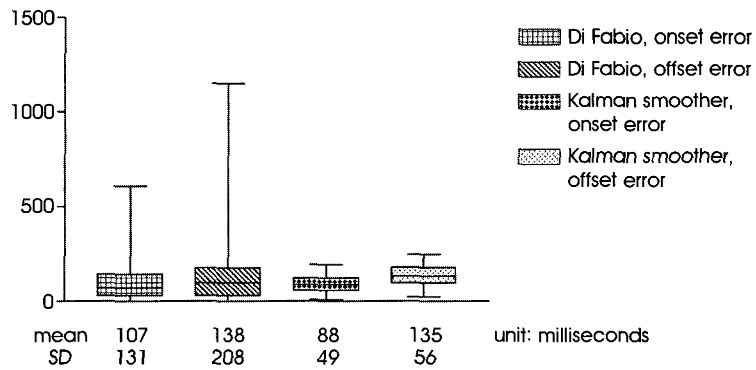

Fig. 13. Quartile of the onset and offset using Di Fabio's method and the Kalman smoother. Both of the mean error and the standard deviation in the Kalman smoother are smaller than both of them in Di Fabio's method.

Kalman smoother are much closer to the results of physical therapist than in Di Fabio's method. Figure 13 represents the details that both of mean and SD have differences and that the Kalman smoother algorithm is better.

Validation of the Kalman smoother algorithm is performed to different 6 muscles; masseter muscle (jaw), sternodleidomastoid muscle (neck), deltoideus muscle (shoulder), soleus muscle (back_leg), tibialis anterior muscle (front leg) and rectus femoris muscle (femur). From table 2 to table 4 represents onset and offset time of these six muscles in each 15 conditions. The mean error of Di Fabio's method is 528.6ms in 1SD condition, 528.4ms in 2SD condition and 401.0ms in 3SD condition. However, the mean error of the Kalman smoother algorithm is 34.3ms. Figure 14 shows results of detection of the onset and offset time in each muscle.

In figure 15, ECG artifacts as the type I (spike) noise is neglected absolutely as like perception of human. To use Di Fabio's algorithm, the onset time is detected as an error at bursting of the ECG artifact. Using the Kalman smoother algorithm, robustness of the type I noise is verified.

Table 2. Results in 1SD, 5ms~25ms conditions. Onset and offset time to be detected of physical therapist, Di Fabio and the Kalman smoother are compared.

		Physical therapist		Di Fabio		Kalman smoother		Di Fabio error		Kalman smoother error	
		onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)
1SD, 5ms	chewing	255	695	362	781	227	702	107	86	28	7
	neck	2450	4125	297	5348	2414	4205	2153	1223	36	80
	shoulder	1300	3750	605	4597	1275	3812	695	847	25	62
	back_leg	1750	4700	1717	4642	1721	4659	33	58	29	41
	front_leg	1250	3300	1277	3289	1246	3297	27	11	4	3
	femur	1300	3850	1331	5713	1294	3760	31	1863	6	90
1SD, 10ms	chewing	255	695	474	652	227	702	219	43	28	7
	neck	2450	4125	297	5348	2414	4205	2153	1223	36	80
	shoulder	1300	3750	605	4597	1275	3812	695	847	25	62
	back_leg	1750	4700	1791	4642	1721	4659	41	58	29	41
	front_leg	1250	3300	1406	3180	1246	3297	156	120	4	3
	femur	1300	3850	1374	5713	1294	3760	74	1863	6	90
1SD, 15ms	chewing	255	695	474	628	227	702	219	67	28	7
	neck	2450	4125	297	5348	2414	4205	2153	1223	36	80
	shoulder	1300	3750	1332	3732	1275	3812	**32**	**18**	**25**	**62**
	back_leg	1750	4700	1791	4642	1721	4659	41	58	29	41
	front_leg	1250	3300	1497	3129	1246	3297	247	171	4	3
	femur	1300	3850	1642	3285	1294	3760	342	563	6	90
1SD, 20ms	chewing	255	695	474	561	227	702	219	134	28	7
	neck	2450	4125	331	5348	2414	4205	2119	1223	36	80
	shoulder	1300	3750	1508	3732	1275	3812	**208**	**18**	**25**	**62**
	back_leg	1750	4700	1791	4068	1721	4659	41	632	29	41
	front_leg	1250	3300	1497	3129	1246	3297	247	171	4	3
	femur	1300	3850	1642	3285	1294	3760	342	565	6	90
1SD, 25ms	chewing	255	695	531	561	227	702	276	134	28	7
	neck	2450	4125	331	3914	2414	4205	2119	211	36	80
	shoulder	1300	3750	1560	3608	1275	3812	260	142	25	62
	back_leg	1750	4700	1821	3811	1721	4659	71	889	29	41
	front_leg	1250	3300	1633	3129	1246	3297	383	171	4	3
	femur	1300	3850	1642	2812	1294	3760	342	1038	6	90
								mean error	528.6ms	mean error	34.3ms

Table 3. Results in 2SD, 5ms~25ms conditions. Onset and offset time to be detected of physical therapist, Di Fabio and the Kalman smoother are compared.

		Physical therapist		Di Fabio		Kalman smoother		Di Fabio error		Kalman smoother error	
		onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)
2SD, 5ms	chewing	255	695	379	699	227	702	**124**	**4**	**28**	**7**
	neck	2450	4125	296	5348	2414	4205	2154	1223	36	80
	shoulder	1300	3750	1301	4599	1275	3812	**1**	**849**	**25**	**62**
	back_leg	1750	4700	1714	4651	1721	4659	36	49	29	41
	front_leg	1250	3300	1319	3266	1246	3297	69	34	4	3
	femur	1300	3850	1374	5714	1294	3760	74	1864	6	90
2SD, 10ms	chewing	255	695	474	652	227	702	219	43	28	7
	neck	2450	4125	296	5348	2414	4205	2154	1223	36	80
	shoulder	1300	3750	1332	3736	1275	3812	**32**	**14**	**25**	**62**
	back_leg	1750	4700	1791	4530	1721	4659	41	170	29	41
	front_leg	1250	3300	1495	3129	1246	3297	245	171	4	3
	femur	1300	3850	1599	5714	1294	3760	299	1864	6	90
2SD, 15ms	chewing	255	695	474	628	227	702	219	67	28	7
	neck	2450	4125	296	5348	2414	4205	2154	1223	36	80
	shoulder	1300	3750	1350	3736	1275	3812	**50**	**14**	**25**	**62**
	back_leg	1750	4700	1867	3329	1721	4659	117	771	29	41
	front_leg	1250	3300	1495	3129	1246	3297	245	171	4	3
	femur	1300	3850	1785	2953	1294	3760	485	897	6	90
2SD, 20ms	chewing	255	695	474	561	227	702	219	134	28	7
	neck	2450	4125	329	3915	2414	4205	2121	210	36	80
	shoulder	1300	3750	1560	3165	1275	3812	260	585	25	62
	back_leg	1750	4700	2132	3929	1721	4659	382	771	29	41
	front_leg	1250	3300	1495	3129	1246	3297	245	171	4	3
	femur	1300	3850	1785	2812	1294	3760	485	1038	6	90
2SD, 25ms	chewing	255	695	531	561	227	702	276	134	28	7
	neck	2450	4125	2789	3876	2414	4205	339	249	36	80
	shoulder	1300	3750	1560	3069	1275	3812	260	681	25	62
	back_leg	1750	4700	2132	3811	1721	4659	382	889	29	41
	front_leg	1250	3300	1629	3129	1246	3297	379	171	4	3
	femur	1300	3850	2216	2812	1294	3760	916	1038	6	90
								mean error	528.4ms	mean error	34.3ms

Table 4. Results in 3SD, 5ms~25ms conditions. Onset and offset time to be detected of physical therapist, Di Fabio and the Kalman smoother are compared.

		Physical therapist		Di Fabio		Kalman smoother		Di Fabio error		Kalman smoother error	
		onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)	onset(ms)	offset(ms)
3SD, 5ms	chewing	255	695	379	683	227	702	124	12	28	7
	neck	2450	4125	319	5360	2414	4205	2131	1235	36	80
	shoulder	1300	3750	1229	3854	1275	3812	71	104	25	62
	back_leg	1750	4700	1774	4603	1721	4659	**24**	**97**	**29**	**41**
	front_leg	1250	3300	1319	3240	1246	3297	69	34	4	3
	femur	1300	3850	1374	3638	1294	3760	74	212	6	90
3SD, 10ms	chewing	255	695	467	652	227	702	212	43	28	7
	neck	2450	4200	1737	4090	2414	4205	**713**	**110**	**36**	**5**
	shoulder	1300	3800	1332	3741	1275	3812	**32**	**59**	**25**	**12**
	back_leg	1750	4700	1791	4534	1721	4659	41	116	29	41
	front_leg	1250	3300	1495	3144	1246	3297	245	156	4	3
	femur	1300	3850	1599	3285	1294	3760	299	565	6	90
3SD, 15ms	chewing	255	695	531	610	227	702	276	85	28	7
	neck	2450	4125	2521	4090	2414	4205	**71**	**35**	**36**	**80**
	shoulder	1300	3750	1350	3170	1275	3812	50	580	25	62
	back_leg	1750	4700	1867	3812	1721	4659	117	888	29	41
	front_leg	1250	3300	1672	2993	1246	3297	422	307	4	3
	femur	1300	3850	1785	2866	1294	3760	485	984	6	90
3SD, 20ms	chewing	255	695	531	561	227	702	276	134	28	7
	neck	2450	4125	2787	3876	2414	4205	337	249	36	80
	shoulder	1300	3750	1560	2985	1275	3812	260	765	25	62
	back_leg	1750	4700	2132	3691	1721	4659	382	1009	29	41
	front_leg	1250	3300	1672	2993	1246	3297	422	307	4	3
	femur	1300	3850	1785	2643	1294	3760	485	1207	6	90
3SD, 25ms	chewing	255	695	599	561	227	702	344	134	28	7
	neck	2450	4125	2787	3876	2414	4205	337	249	36	80
	shoulder	1300	3750	1684	2985	1275	3812	384	765	25	62
	back_leg	1750	4700	2132	3346	1721	4659	382	1354	29	41
	front_leg	1250	3300	1672	2993	1246	3297	422	307	4	3
	femur	1300	3850	2438	2467	1294	3760	1138	1383	6	90
								mean error	401.0ms	mean error	34.3ms

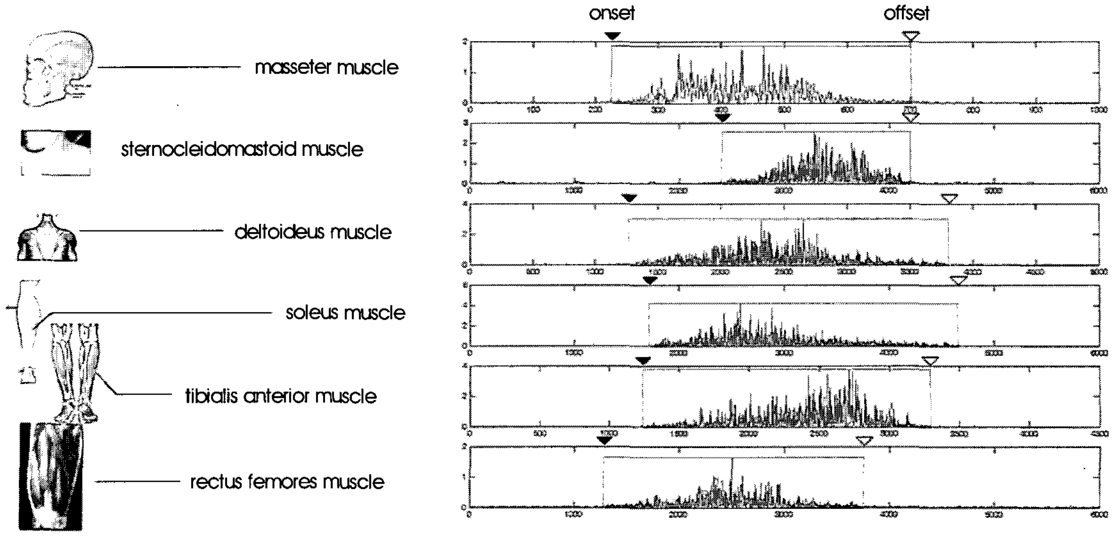

Fig. 14. Some examples of detection of onset and offset time in different muscles.

		Di Fabio error		Kalman smoother error	
		onset(ms)	offset(ms)	onset(ms)	offset(ms)
3SD, 10ms	chewing	212	43	28	7
	neck	713	110	36	5
	shoulder	32	59	25	12
	back_leg	41	166	29	41
	front_leg	245	156	4	3
	femur	299	565	6	90

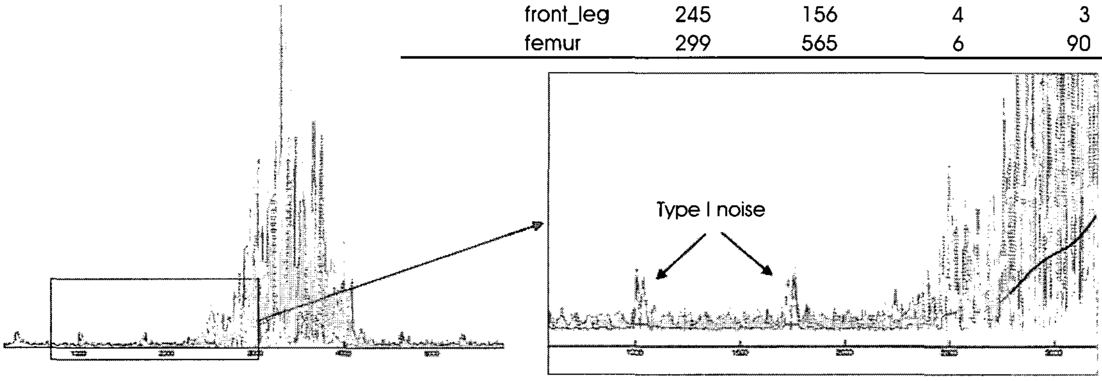

Fig. 15. Robustness to ECG artifacts as type I noise in EMG signals. To use the Kalman smoother, the spiky noise is neglected absolutely.

V. CONCLUSION

The Kalman smoother algorithm is very robust to the type I noise like a spike. In this case, the type I noise is an ECG signal that shares its frequencies with EMG signal. Because of the Kalman smoother represents trends of signals well, spiky noise can be neglected as well as an ability to extract trends from signals by perception of human.

In the aspect of error compared with clinical experts, the Kalman smoother algorithm has higher performance in the means and standard deviations than Di Fabio's algorithm. Input signals in Di Fabio's algorithm must form the Gaussian distribution. Otherwise, the algorithm is able to detect onset or offset time at different time when some artifacts are bursted. On the other hand, the Kalman smoother algorithm does not be influenced for about any types of signal.

The standard deviation of the results has a clear boundary between Di Fabio's algorithm and the Kalman smoother algorithm. Because of lack of accuracy and generality in Di Fabio's algorithm, its results are distributed from place to place.

Finally, process of experiments is very complex and troublesome in Di Fabio's algorithm compared to the Kalman smoother algorithm.

REFERENCES

[1] Carlo J. De Luca, "The use of surface electromyography in biomechanics," *Journal of Applied Biomechanics*, vol. 13, pp. 135-163, 1997.

[2] S. Micera, G. Vannozzi, A.M. Sabatini, and P. Dario, "Improving detection of muscle activation intervals," *IEEE Engineering in Medicine and Biology Magazine*, 2001.

[3] Richard P. Di Fabio, "Reliability of computerized surface electromyography for determining the onset of muscle activity," *Physical Therapy*, vol. 67, pp. 43-48, 1987.

[4] Jacquelin Perry, *Gait Analysis: Normal and Pathological Function*, Delmar Learning, 1992.

[5] G.W. Lange, R.A. Hintermeister, T. Schlegel, et al., "Electromyographic and kinematic analysis of graded treadmill walking and the implications for knee rehabilitation," *The Journal of Orthopaedic and Sports Physical Therapy*, vol. 23, pp. 294-301, 1996.

[6] E.J. Cowling, J.R. Steele, "The effect of upper-limb motion on lower-limb muscle synchrony: Implications for anterior cruciate ligament injury," *Journal of Bone and Joint Surgery: American volume,* vol. 83, pp. A:35-41, 2001.

[7] R.T. Lauer, C.A. Laughton, M. Orlin and B.T. Smith, "Wavelet decomposition for the identification of EMG activity in the gait cycle," *IEEE,* pp. 142~143, 2003.

[8] Y.H. Lee, S.I. Jeon, C.I. Park, "Properties of the human skeletal muscles revealed by frequency analysis of muscular action potentials during voluntary contraction," *Korean Academy of Rehabilitation Medicine*, vol. 18, pp. 311-327, 1994.

[9] G.T. Allison, "Trunk muscle onset detection technique for EMG signals with ECG artefact," *Journal of Electromyography and Kinesiology*, vol. 13, pp. 209-216, 2003.

[10] Andrea Merlo, Dirio Farina, and Roberto Merletti, "A fast and reliable technique for muscle activity detection from surface EMG signals," *IEEE Transactions on Biomedical Engineering,* vol. 50, pp. 316-323, 2003.

[11] Greg Welch and Gary Bishop, *An Introduction to the Kalman Filter*, North Carolina: USA, Chapel Hill, 2004.

[12] R.E. Kalman, "A New Approach to Linear Filtering and Prediction Problems," *Trans. ASME-J. Basic Engr.*, pp. 35-45, 1960.

[13] Mohinder S. Grewal and Angus P. Andrews, *Kalman Filtering Theory and Practice*, PRENTICE HALL, 1993.

[14] Robert Grover Brown and Patrick Y.C. Hwang, *Introduction to Random Signal and Applied Kalman Filtering*, Wiley, 1997.

[15] Y.J. Chung, S.H. Cho, J.H. Lee and S.H. Lee, "Reliability of the onset time determinations during maximal isometric contraction in surface EMG," *Korean Academy of University Trained Physical Therapists*, vol. 1, pp. 51-62, 2003.