An Automated Motion Artifact Removal Algorithm in Electrocardiogram Based on Independent Component Analysis

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Abstract— **Mobile ECG recordings are widely used to monitor abnormality of the cardiovascular system during daily life. However, ambulatory ECG recordings are often contaminated by many types of artifacts. In motion artifacts removal, because ECG and movement are not always independent, ICA based noise reduction may distort the signals. Thus, this paper introduces automatic noise detection and removal technique based on independent component analysis (ICA) preventing the signal distortion and attenuation. Using several proposed decision rules, 3-channel ECGs are analyzed their noisiness and Gaussianity to predict whether motion artifacts and ECGs can be separated and reconstructed without distortion. This method is evaluated by ECGs recorded during 0 to 7km/h rest, walking, and running exercise. Finally, its performance is compared to the conventional approaches of ICA-based noise reduction in ECGs. As results, the reconstructed ECGs by the proposed algorithm show higher correlation with estimated reference signals and there is no distortion in reconstruction of the signals.**

Keywords-Independent component analysis; Motion artifact; ECG; Noise removal

I. INTRODUCTION

Electrocardiogram (ECG) monitoring provides useful information to diagnose, evaluate, and treat cardiovascular related diseases. Conventionally, patients visited hospital, where the measurement devices and the physicians are available, to acquire the ECG for detecting abnormality of the cardiovascular system. However, this approach involves temporal and spatial limitation for the measurement, because it is only possible when patients visit the hospitals. For this reason, many portable devices measuring the signal everyday have been researched and commercialized. But, it still has challenge, the ECG recording is exposed to many types of environmental noise such as power-line interference and motion artifacts in long-term acquisition. Furthermore, in many cases of the ECG analysis, manual classification between motion artifacts and other events such as arrhythmia by cardiologists is intensive and time-consuming task [1]. Overcoming the limitation, many noise reduction algorithms have been introduced and applied to the ECG recording. The technique of adaptive filter for motion artifacts removal, which uses acceleration signals as references, has widely applied for the ambulatory ECG measurements [2-3]. However, low correlation values between complicated body movements during activities and acceleration signals restrict the use of the techniques. Independent component analysis (ICA) [4] has provided an effective method in the application of motion artifacts cancellation by assuming ECG and motion artifact are independent [5]. Practically, multi-channel ECGs with motion artifacts (mixture signals) are decomposed to motion artifacts and ECG components (source signals) which are relatively high correlated among each channel based on the matrix that maximizes the non-Gaussianity of mixture signals. Thus, the noise removal in ambulatory multi-channel ECG recording is possible by elimination of one source signal that is estimated to motion artifact. Applications of the ICA for motion reduction in ECG recordings have been introduced in many researches of which the algorithms automatically select and remove motion artifact in decomposed independent components [6-7]. However, the ICA also has drawbacks. For the actual measurement, the motion artifacts and ECG are not exactly independent, i.e. cardiac dynamics such as heart rate and ECG morphology are affected by body movements for instance, Head Down Bed Rest maneuver [8]. Moreover, the ICA is limited on non-Gaussian random variables. Thus, in the case of mixture signals which follow the Gaussian property, applying the ICA is not suitable, further it might cause signal distortion by eliminating meaningful information.

This paper is motivated by the above challenges: 1) automated noise detection from the acquired ECGs 2) automatic motion artifact component selection and removal from decomposed signals considering interdependency between ECG components and motion artifacts, 3) prediction of whether the multi-channel ECGs with motion artifacts can be decomposed or not before applying the ICA. In this paper, we present automated motion artifact removal algorithm based on ICA, which prevents reconstructive distortion and considers correlation between multi-channel ECGs and motion artifacts with several decision rules.

II. MATERIALS & METHODS

Fig. 1 shows schematic of motion artifact reduction algorithm. It basically consists of 5 parts: noise detection, signal status check, ICA, de-noising and reconstruction.

Noise detection is the first layer that filters unnecessary signals, such as clean ECGs. To check the signal status predicts whether the motion artifacts and ECGs will be separated by the ICA or not. It is based on properties of the ICA. Through this process, we can avoid signal distortion which the necessary component is removed in the reconstruction process. After the ICA, estimated motion artifacts which show low cross correlation coefficient among the components are eliminated. Then, finally we can observe de-noised ECG signals.

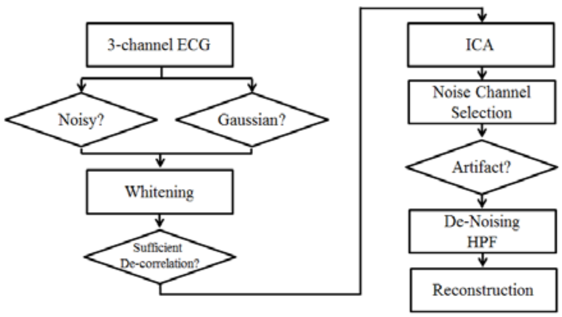

Fig. 1. Shematic of motion artifact removal algorithm.

A. *Data Collection*

The data was acquired from the portable device that is attached on the subject's chest. 3-channel ECGs (Lead1, Lead2, v2) were recorded simultaneously from 5 healthy subjects (5 male, 28.2±2.68) during the rest, 2, 4, 5km/h walking and 6, 7km/h running on a treadmill. Every exercise trial contains 5 seconds recording in rest state. Each experimental data was acquired over a minute with 500Hz sampling rate and transferred to the PC using the Bluetooth. The measured data were segmented by the corresponding data in 5 seconds. The proposed algorithm was applied to each segmented data.

B. *Noise Detection*

ECG shows different characteristics depending on patients. Furthermore, motion artifacts are differently influenced to the ECG recordings. Therefore, the noise detection should be accessed with individual property. Here, we compared ambulatory ECGs to the reference ECGs that were recorded before the exercise.

The Central Limit Theorem explains that the distribution of a sum of random variables tends toward a Gaussian distribution [4]. Therefore, ECGs during the exercise which contains motion artifacts are closer to Gaussian distribution. Thus, using negentropy (explained in *section C.*) which is one measure of non-Gaussianity, rest ECGs and ambulatory ECGs are compared. Proposed decision rule for detecting noisy ECG is as follows:

$$\alpha_k \times J_{ref}(k) > J_{test}(k) \tag{1}$$

where,
$J_X(k)$: *Approximation of negentropy for* k^{th} *channel ECG*
α_k: *postive constants, here* 0.8

C. *Gaussianity*

The fundamental limitation in the ICA is that the independent components must be non-Gaussian [4]. Eq. (2) shows joint density of x, y which are Gaussian variables with zero mean and unit variance.

$$p(x,y) = p(xy) = \frac{1}{2\pi} e^{\left(-\frac{x^2+y^2}{2}\right)} \tag{2}$$

In this case, the density is symmetric. Therefore it does not contain any information on the directions of the columns of the mixing matrix A [4].

The classical measure of non-Gaussianity is kurtosis, the fourth-order moment defined by

$$K(x) = E[x^4] - 3(E[x^2])^2 \tag{3}$$

Kurtosis is zero for a Gaussian random variable. However, it can be very sensitive to outlier [4, 9].

Negentropy which is based on informatics is another estimation of non-Gaussianity defined by Eq. (4).

$$J(\mathbf{x}) \;=\; H(\mathbf{x}_{gauses}) - H(\mathbf{x}) \tag{4}$$

$$H(\mathbf{x}) \;=\; -\int f(\mathbf{x}) \log f(\mathbf{x}) f\mathbf{x} \tag{5}$$

where, $\mathbf{x}_{gauss}$ is a Gaussian random variable of same covariance matrix as $\mathbf{x}$. However, its computational complexity, some approximations are used. Here, we adapted the approximation developed in [10]:

$$J(x) \approx \sum_{i=1}^{p} k_i (E[G_i(x) - E[G_i(v)])^2 \tag{6}$$

where,
k_i: *positive constants,* here k_i =1
v : a Gaussian variable of zero mean and unit variance

G is selected that have proved very useful:

$$G_1(w) = \frac{1}{a_1} \log\cosh a_1 w, \qquad G_2(w) = -e^{\left(-\frac{w^2}{2}\right)} \tag{7}$$

where, $1 \le a_1 \le 2$ *, here* $a_1 = 1$

The main purpose of the Gaussianity check is to give limitation for the suggested algorithm to eliminate chances that ECG components would be removed on the de-nosing process and the signals distorted. If the random variable is Gaussian, negentropy is zero. Thus, we give threshold of .00005 for the second rule. If the approximation of negentropy for each ECG is lower than the threshold, the signal is regarded as Gaussian, then the algorithm stops processing and returns the original ECGs.

D. *Whitening*

Whitening is a useful pre-processing before the ICA obtaining de-correlated data. In other words, covariance matrix of the de-correlated data equals the identity matrix.

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One popular method for whitening is to use eigenvalue decomposition.

In probability distribution aspect, de-correlation means probability distribution spreads out of mean value. Thus, we can decide whether mixture signals of ECG and motion artifact would be decomposed or not, by observing whitening results. Decision rule is as follow:

$$D_w = P_W(w) - P_M(m) \tag{8}$$

$$-a \leq w \leq a, -a \leq m \leq a$$

$$if, D_w > .01, go\ to\ next\ step$$
$$otherwies, stop\ processing$$

E. ICA

The ICA provides solution to find independent source signals *s* from the mixture signals *x*. It could be expressed as a linear equation with vector formation:

$$X = AS \tag{9}$$

where, S is source signals, X is observed mixture signals and A is transformation matrix. The idea of ICA is simple that S is statistically independent. From the Eq. (9), its inverse form is acquired:

$$S = W^T X \tag{10}$$

where, W is inverse of A matrix. With the assumption of ICA, W matrix should be set in direction to maximize independency of X. It means that W matrix is updated to maximize non-Gaussianity of mixture signals. There are several approaches in ICA such as Fast-ICA and Joint Approximate Diagonalization of Eigen-matrices (JADE) algorithm. Here, we chose JADE algorithm which consists of orthogonalization and rotation with advantage of avoidance convergence problem, fast processing and efficiency [11-13].

F. Noise Channel Selecion and Denoising

After the ICA, motion artifacts channel selection is required from the independent source signals to remove unnecessary component for the ECG reconstruction. Because motion artifacts have low correlation with ECG, it can be selected by Eq. (10).

$$r_{xy}(k) = \frac{E[(X_n - \mu_x)(Y_{n+k} - \mu_y)]}{\sigma_x \sigma_y} \tag{11}$$

Basic assumption of motion artifacts removal using ICA is that motion artifacts and ECG are independent. Therefore both signals should be completely separated under the condition. However, because the movements influence cardiac dynamics, it cannot be said ECG and motion artifacts are always and fully independent. Fig. 2 shows the independent components decomposed by the ICA. In Fig. 2 (a), estimated motion artifacts and QRSs are not completely separated. To overcome this problem, we applied the high pass filter with cutoff frequency 15Hz to selected channel instead of which motion artifacts component set to zero.

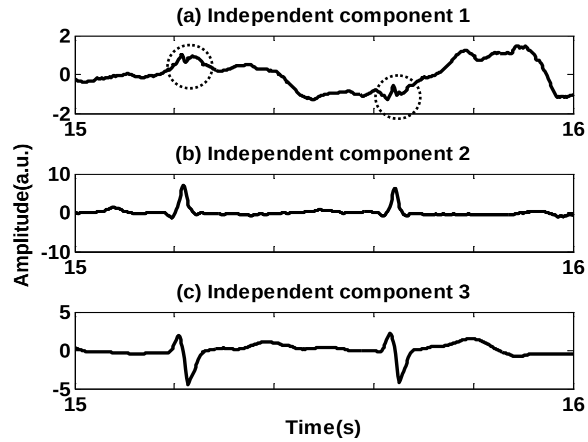

Fig. 2. Independent components decomposed from the 3-channel ECGs during exercise. (a) shows estimated motion artifacts with the rest of ECG components.

G. Analysis

A major problem of ECG signal processing is that it is almost impossible to measure ECG and motion artifacts separately during the movement. Thus, even though ECG is de-noised by the certain motion removal technique, quantitative analysis is limited without the reference signal.

In ensemble average, N sets of data are averaged together with fixed time *t* to reduce random fluctuations in the signal. From the measured ECGs in each trial, R-peaks are manually marked and set to central position of the ensemble with the size of 501 samples for each channel of ECG. R-peak-centered ensembles are averaged to acquire representative ECG waveform which regarded as the reference signal.

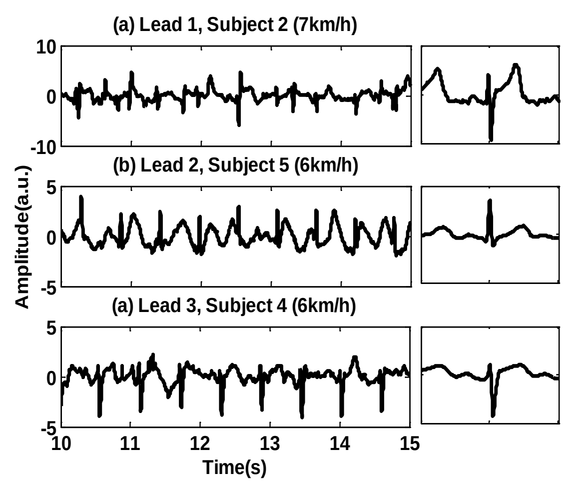

Fig. 3. Time series noisy ECG in each channel and its ensemble average signal. 501 sample ensemble average signals in each trial are set to the reference signals that are compared to processed signals.

Fig. 3 shows the results of the ensemble average for ambulatory ECGs. By the average, motion artifacts which show random fluctuation property are attenuated and relatively regular and deterministic ECGs remain. Thus, we regard the ensemble averaged signal as the reference for the trial and compute cross correlation coefficient among the reference signal and the results of signals based on proposed and conventional methods.

III. RESULTS

Fig. 4 and Fig. 5 show examples of ECGs with motion artifacts (on the left side). For the cases, suggested algorithm removes both motion artifacts. The results are shown on the right side of each Fig.

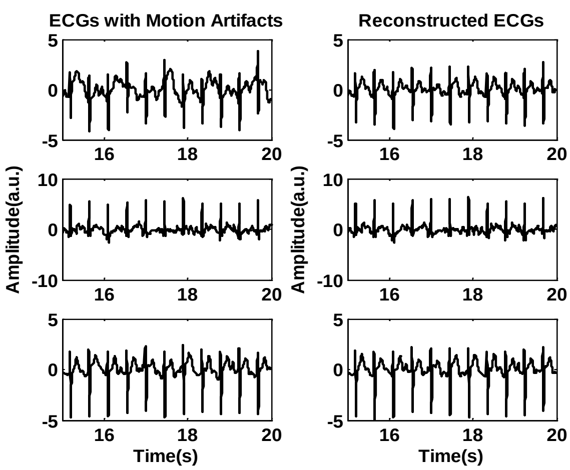

Fig. 4. An example of ECGs (Lead1, Lead 2, and v2 from the top) during exercise and reconstructed ECGs. Distorted T-waves and fluctuation in the Lead 1 ECG restored by the algorithm.

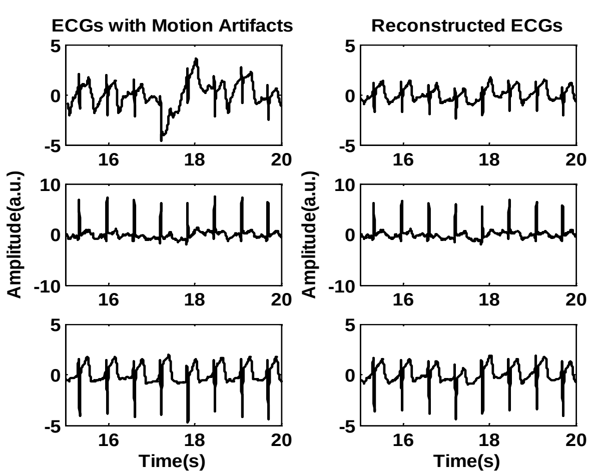

Fig 5. An example of ECGs (Lead1, Lead 2, and v2 from the top) during exercise and reconstructed ECGs. Sudden movement in the Lead 1 ECG restored by the algorithm.

Table 1 presents the mean value of cross correlation coefficients among estimated reference signals and the processed signals that were followed each processing path. 'Reconstruction' means the ECGs were noisy, non-Gaussian and, sufficiently whitened, thus, ICA was applied to remove motion artifacts. 'Low Gaussianity' means that the measured signals were noisy but, followed the Gaussian distribution. Therefore, ICA was not applied and the original signals were returned. Likewise, in the case of 'Insufficient Whitening', the algorithm moves onto the next segment data. The results arranged for the proposed algorithm (Prop.), conventional method (Con.), modified conventional method (*m*Con.) which is based on conventional method, but estimated noise vector is filtered by 15Hz BPF, not set to zero, and '*c*Prop.' which is based on the Prop., but estimated noise vector is set to zero. Thus, the results belonging to the 'Low Gaussian-Prop.' and 'Insufficient Whitening-Prop.' present cross correlation coefficients between the original signals and estimated reference signals. On the Table 1, reconstructed ECGs from our method show high correlation with the estimated reference signals with low variance. Fig. 6 shows the reconstructed Lead 1 ECG which underwent 'Prop.'(*Thick line)* and '*m*Con.'(*Thin line*). The ECG from the 'Prop.' displays less attenuated QRS and restored T-wave.

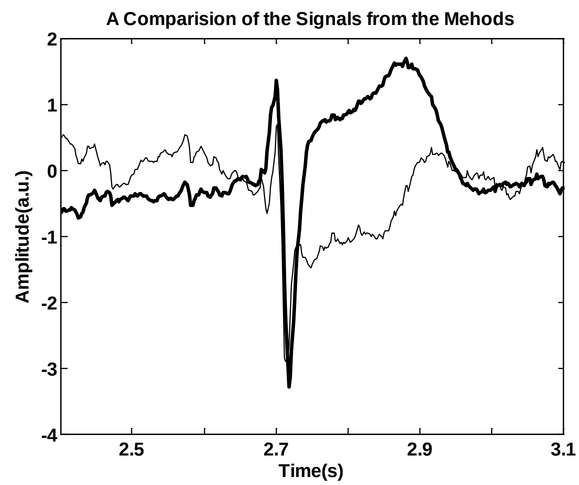

Fig. 6. A comparison of restored Lead 1 ECG from 'Prop.'(*Thick line)* and '*m*Con.'(*thin line*). The signal followed by the proposed algorithm shows less attenuated QRS and restored T-wave.

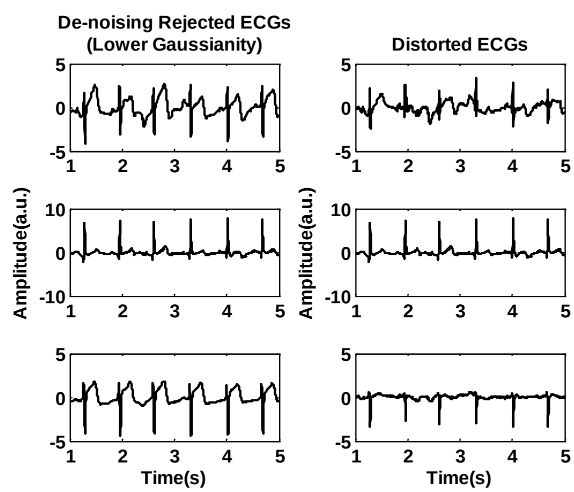

Fig. 7. Processed ECGs that are applied two different methods ('Prop.' on the left side and 'Con' on the right side) .

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TABLE I. THE RECONSTRUCTION RESULTS OF THE ICA BASED NOISE REMOVAL ALGORITHMS

		Reconstruction				Low Gaussianity				Insufficient Whitening			
		Prop.	*Con.*	*mCon.*	*cPorp.*	*Prop.*	*Con.*	*mCon.*	*cPorp.*	*Prop.*	*Con.*	*mCon.*	*cPorp.*
S1	**L1**	.909	.846	.947	.845	.384	.781	.383	.644	-	-	-	-
	L2	.910	.902	.910	.906	.667	.736	.669	.738	-	-	-	-
	v2	.962	.849	.965	.904	.639	.816	.639	.807	-	-	-	-
S2	**L1**	.876	.306	.865	.397	.798	.436	.798	.501	-	-	-	-
	L2	.932	.940	.928	.942	.936	.933	.936	.934	-	-	-	-
	v2	.957	.486	.955	.591	.969	.552	.969	.636	-	-	-	-
S3	**L1**	.858	.855	.855	.853	.671	.566	.671	.569	.931	.789	.931	.885
	L2	.857	.839	.839	.852	.753	.757	.753	.743	.941	.935	.941	.917
	v2	.875	.863	.863	.871	.764	.485	.764	.521	.974	.705	.974	.863
S4	**L1**	.860	.766	.857	.796	.331	.363	.331	.376	-	-	-	-
	L2	.926	.918	.924	.922	.344	.326	.344	.397	-	-	-	-
	v2	.949	.917	.947	.930	.826	.859	.826	.859	-	-	-	-
S5	**L1**	-	-	-	-	.560	.613	.560	.619	-	-	-	-
	L2	-	-	-	-	.599	.679	.599	.701	-	-	-	-
	v2	-	-	-	-	.779	.771	.779	.775	-	-	-	-

Fig. 7 presents processed ECGs that is applied two different methods. ECGs on the left side were processed through the proposed algorithm. Even though the signals are slightly noisy, because the each ECG follows the Gaussian distribution, the ICA is not applied for the signals. On the other hand, ECGs on the right side were applied the ICA without any decision rules. After the ICA, the component which has the lowest kurtosis value is estimated to the noise component and set to zero. Then, necessary component can be eliminated. Finally, reconstructed signals are distorted as shown in Fig. 7.

IV. Discussion

In order to evaluate our propose algorithm, ambulatory ECGs were acquired and applied, and the algorithm is compared with several methods including normally used algorithm. Since our goal was to eliminate the motion artifacts in ECGs without distortion, several decision rules were applied and evaluated their efficiency.

The ICA is popular blind source separation technique which has provided reliable solution for noise reduction problem in the ECG. According to the ICA, observed signals are separated to the independent sources by decomposing the mixture signals with direction to maximize non-Gaussianity. One important characteristics of the ICA is that the method is restricted to Gaussian random variable. Traditional assumption in ECG de-noising is that ECG and motion artifact are statistically independent corresponding to basic assumption of the ICA. However, movements influence to cardiac dynamics, thus it is not always satisfied. Furthermore, ICA based motion removal algorithm may distort ECG signals by eliminating important components. Thus, we proposed 4 decision rules to avoid above limitation. Noisiness and Gaussianity were considered by approximation of negentropy which shows zero for the Gaussian random variable under condition of the Central Limit Theorem. Because the distribution of a sum of random variables follows a Gaussian distribution, if the approximation of negentropy for ECG during exercise is decreased compared to the signal during rest, the segment of the signal regarded as noisy signal. Also, if the approximation of negentropy closes to zero, it is considered to the Gaussian variable. Under this condition, the algorithm regards it as out of processing range, and moves onto next segment of data.

Whitening is useful processing before the ICA. Through the process, observed random vector is uncorrelated and its variance equals unity. In the probability distribution aspect, it means that the distribution moves outside of mean value. If the distribution of the whitening result shows similarity with the distribution of the input random vector, it can be said vector is already uncorrelated. In this case, the algorithm also decides to stop processing and starts with next segment of data. After the ICA, motion artifact component was found using cross correlation coefficient. The channel which has the lowest correlation with each other was selected and filtered. To consider motion artifact and ECG were not perfectly separated, we applied HPF to selected component, not set to zero.

The algorithm was compared with several approaches to evaluate implications of the proposed method such as applying filter and decision rules. One of important problems in ambulatory ECG analysis is absence of reference signal. In this research, R-peak centered ensembles were generated and averaged data regard as the reference signal of each trial. Ambulatory ECGs in Fig. 3 are highly contaminated with motion artifacts (on the left side), but most of noise component are eliminated on the averaged signals (on the right side).

For the results shown in Table 1, our proposed method showed higher correlation with the reference signal. In some results presented better results than our algorithm, such as result from S1 using modified conventional method (‘*m*Con.’). However, stability which is based on variation of the results for the all results proves the proposed algorithm covers large range of movements for various subjects. The results 'Low Gaussian-Prop.' means cross correlation coefficient between observed ECGs and reference signals, because the algorithm detected the signals are Gaussian variables and returned original signals. These results can be regarded standard for 'Low Gaussian- '. Thus the results that are lower than this standard are explained that ECGs were distorted by the applied method such as 'Low Gaussian-Con.' of the subject 3. Also, there are the results that have high variation among the channels, such as 'Low Gaussian-Con.' of the subject 4. It is considered that the necessary components were eliminated during de-noising shown in Fig. 7, for instance.

It is not sufficient to compare the processing results with only one parameter. Therefore, it is needed to establish parameters which measure the degree of distortion.

In summary, we proposed motion artifact removal algorithm using the ICA that minimizes distortion. It is also expected to reduce processing rate by jumping over unnecessary processes. Moreover, the method which is based on short-term segmented dataset offers potential for real-time processing this algorithm.

V. CONCLUSION

In summary, proposed method successfully removed the motion artifacts in ambulatory ECGs without distortion. Furthermore, reconstructed ECGs processed by this method showed higher correlation with the estimated reference ECGs than the signals processed by other methods. Because the proposed algorithm jumps over unnecessary process, it is expected to reduce processing rate. In addition, the method which is based on short-term segmented (5 seconds) dataset offers possibility for real-time processing of ECG. Finally, the proposed algorithm has potential to be applied for long-term ECG monitoring in daily life.

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