34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Assessment of Photoplethysmogram Signal Quality using Morphology Integrated with Temporal Information Approach

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Abstract— **Photoplethysmograph (PPG) signal measured from wearable devices for tele-home healthcare is often corrupted by motion artifacts which often cause false extraction of physiological features and lead to erroneous medical decision for monitoring. In this paper we propose an innovative method which combines the morphological characteristics with temporal variability information in the signal series to assess the signal quality and to reject the meaningless segments that are significantly contaminated by artifacts aiming at improving the accuracy of derived vital physiological features. Experimental results using PPG signals collected in our lab demonstrate that our mechanism can achieve an accuracy of 98.92%.**

I. INTRODUCTION

Tele-home healthcare can benefit from wearable biosensors which provide a noninvasive,telemetric and flexible way to monitor physiological status [1]. Plethysmography (PPG) signals measured from a ring sensor can serve as a physiological signal to derive the vital features such as blood oxygen saturation, heart rate ,respiratory rate and blood pressure which indicate the person's physiological status [2]. However robust feature extraction from PPG signal under an arbitrary ambulatory environment still remains a challenge. The difficulties stem from the fact that PPG signal is vulnerable to the finger and arm movement and could be corrupted by the motion artifacts significantly which will cause false detection of vital signs and lead to false alarm and erroneous medical decision. Signal quality estimation and artifact rejection become a critical issue in guarantee of reliable physiological status monitoring.

Some signal quality estimation methods have been developed based on signal quality index such as ECGSQI [3] and ABPSQI [3], [4], [5] which provide the Signal Quality Estimates (SQE) of ECG signals and ABP signals. Method described in [6] use Hjorth parameters [7] to identify abnormal PPG pulses. These methods either use the shape information or explore the temporal variability to evaluate the signal quality. In our study, we integrate the morphological characteristics with the variability in time series of the signal to determine the signal quality level and to reject the artifacts. Results on the experimental data showed our method can grade the signal quality effectively.

This work was supported by NSFC (Grant No. 61002002); National Basic Research Program 973 (Grant No. 2010CB732606) from Ministry of Science and Technology, China; The Guangdong Innovation Team Fund (Low-cost Health Technology Innovative Team), China; Overseas Scientists Innovation Team Fund, Chinese Academy of Sciences and Key Lab of Health Informatics of Chinese Academy of Sciences; Shenzhen Public Platform for Biomedical Electronics and Health Informatics.

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II. SIGNAL QUALITY ASSESSMENT

In our proposed Morphology INtegration with Temporal information approach (*MINT* approach) as shown in Fig. 1, we perform segmentation to the signal and then detect the promising features which are considered to be related to the signal quality. After extraction of the morphology indicators we analyze morphology by two metrics and obtain the quantified degree of segment deformation by measuring the similarity with a template signal based on dynamic time warping. We use a Kalman filter to track the time varying characteristics of the segment simultaneously. We then integrate the morphology with temporal variability information to evaluate segment quality and update the Kalman filter according to the features validation result. This adaptive procedure will be carried on iteratively and the signal quality assessment result will be generated recursively. Finally, we can grade the signal quality into four levels:

- Level 1: good quality segment with useful extracted features and normal morphology
- Level 2: valid segment with useful extracted features but problematic morphology
- Level 3: invalid segment with erroneous features
- Level 4: total corrupted segment

In our study, we would make an assumption that there're no transient pathology changes in the features of interest.

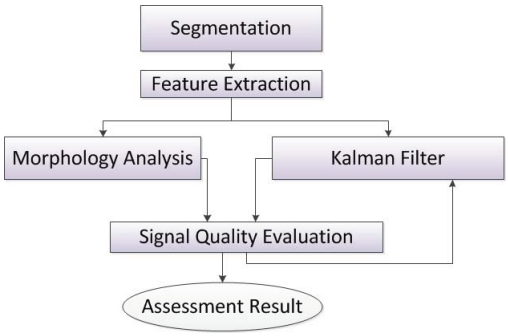

Fig. 1. Block Diagram of the Morphology Integration with Temporal information approach

A. Segmentation

We find the most significant feature point in the waveform and then extract the periodic waveform. We perform a 25 points moving average filter to the original signal and find

all the local maximal extremum in this preprocessed version. An adaptive refractory period value and the mean envelope value are employed to locate the systolic peaks. We use the maximal second derivative approach mentioned in [8] to find the pulse onset in the original signal between the adjacent systolic peaks. The signal will be then segmented according to these onset points.

B. Feature Extraction

After obtaining the periodic signal, we begin to extract the features which are considered to be related to signal quality for each segment. Based on the fact that the pulse in PPG waveform consists of the anacrotic phase which corresponds with systole and the catacrotic phase with diastole and wave reflections from periphery [1], the cases shown in Fig. 2(a) and Fig. 2(b) will be taken as normal segment due to individual differences.

We seek the dicrotic notch and the dicrotic peak if there're only one oscillation existed in the downstroke and calculate the parameters h1, h2, h3 shown in Fig. 2(a). In each segment we find all the peaks which exceed the mean envelope and record them into set Φ_1. The peak interval and the onset duration will also be calculated as features for further analysis.

C. Morphology Analysis

1) Metric I: We analyze the morphology of segment using two metrics. Once the extracted features are ready, we firstly analyze the set of peaks Φ_1 and the dicrotic notch (if exists) based on the number of peaks and the relation between parameters h1, h2, h3 in order to discriminate the bad segment with shape pattern shown in Fig. 2(d). We obtain initial morphology analysis result and the extracted feature information at the end of this step. We trash the bad segment and pass those with pattern as shown in Fig. 2(a)-Fig. 2(c) to further analysis.

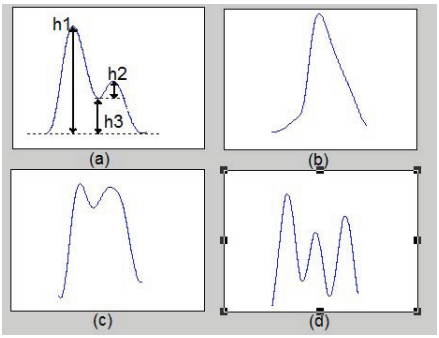

Fig. 2. Signal Patterns and Morphology Analysis using Metric I: (a) clean segment with a dicrotic notch, marked as normal morphology; (b) clean segment without a dicrotic notch, marked as normal morphology; (c) segment marked as bad morphology; (d) useless corrupted segment labeled as Level 4

2) Metric II: We utilize one entire period of the clean PPG data collected from the same person under same measurement condition as the template signal which can identify the most typical periodic PPG waveform. We adjust the morphology evaluation results by measuring the similarity degree between the template signal and each of the segments marked as normal from Metric I analysis.

The Dynamic Time Warping (DTW) method can effectively be applied to measure the similarity between two time series with different lengths and paces by aligning samples. We employ an improved version named as the Derivative Dynamic Time Warping (DDTW) [9] approach which considers the shape (trend) information to quantify the similarity between the segment X and the template signal Y of length n and m respectively by calculating the DTW distance, where X=$x_1, x_2 ... x_n$ and Y=$y_1, y_2 ... y_m$. The first derivatives can be estimated using the following formulation proposed in [9]:

$$x_i^{'} = \frac{(x_i - x_{i-1}) + ((x_{i+1} - x_{i-1})/2)}{2} \tag{1}$$

The distance function $d_{i,j}$ between sample x_i and y_j is defined as

$$d_{i,j} = (x_i^{'} - y_j^{'})^2, \tag{2}$$

where $x_i^{'}$ and $y_j^{'}$ can be calculated by (1) which represent the i^{th} and j^{th} elements in the first derivative of X and Y respectively.

The matching cost (or the DTW distance) between sample x_i and y_j can be computed based on dynamic programming:

$$D(i,j) = d_{i,j} + min \begin{Bmatrix} D(i,j-1) \\ D(i-1,j) \\ D(i-1,j-1) \end{Bmatrix} \tag{3}$$

where $d_{i,j}$ is computed by (2)

After the determination of optimal aligning, we sum up the warping cost along the optimal path which is carried out by (3) to derive a total cost χ. The larger χ indicates a higher dissimilarity between the analyzed segment and the template. It depicts a serious deformation when χ exceeds a predefined threshold ξ_{dissim}. We reinforce the morphology discrimination by marking those segments which reveal great distinction from the template signal as abnormal morphology.

D. Signal Quality Evaluation

We apply a Kalman filter [10] to inspect four selected features: the duration length D_k of the segment, the peak-to-peak interval length T_k, the height M_k from onset to peak of the segment, and the y-axis location Y_k of onset. We incorporate the morphology evaluation result from previous step in additions to the residual information during estimation to determine the validness of the extracted features and update Kalman filter accordingly.

In our modeling system, the state equation is defined as:

$$x_k = \begin{bmatrix} D_k \\ T_k \\ M_k \\ Y_k \end{bmatrix} \tag{4}$$

The state model can be reduced to:

$$x_k = F_k x_{k-1} + B_k u_k + w_k \tag{5}$$

and

$$z_k = H_k x_k + v_k \tag{6}$$

where F_k is the state transition model, B_k is the control-input model, H_k is the observation model, and $w_k \sim N(0, Q_k)$ is the process noise, $v_k \sim N(0, R_k)$ is the observation noise, with Q referring to process noise covariance and R referring to observation noise covariance respectively.

The state transition matrix F and the measurement matrix H are both set to 4x4 identity matrix, while the process noise covariance matrix Q and the control input model B with control vector u are set to zero under the assumption that the system is in a steady-state condition and we have total confidence in the system model. The noise covariance R is set by computing the covariance of the four features extracted from the good quality signals acquired under stationary measurement.

$$R = \begin{bmatrix} C_1 & 0 & 0 & 0 \\ 0 & C_2 & 0 & 0 \\ 0 & 0 & C_3 & 0 \\ 0 & 0 & 0 & C_4 \end{bmatrix} \tag{7}$$

where C_1-C_4 correspond with the four selected features respectively.

Then the prediction of the next state before measurements are carried out as follows:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \tag{8}$$

where $\hat{x}_{k-1|k-1}$ refers to a priori state estimation.

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{9}$$

where $P_{k-1|k-1}$ refers to a priori estimation covariance.

The measurement residual then can be calculated as:

$$\tilde{\gamma} = z_k - H_k \hat{x}_{k|k-1} \tag{10}$$

where $\hat{x}_{k|k-1}$ is the predicted state estimate derived from (8).

We exploit four flexible threshold ξ_{odresi},ξ_{piresi},ξ_{phresi} and ξ_{olresi} which correspond to the four features separately with morphology analysis result to form the determination rule. We classify the four features into two categories Ψ_1 and Ψ_2. Features in Ψ_1 may vary due to the physiological changes or the motion artifacts such as D_k and T_k. We adjust the corresponding threshold according to the morphology analysis result to judge the validness of features in Ψ_1 and still proceed to update the system model on the premise of good morphology even if the residual analysis results suggest a temporal exception, otherwise the features of the segment will be regarded as invalid.

We will forbid the update when the innovative measurement is untrustworthy, otherwise we update the system use the following formulation:

$$S_k = H_k P_{k|k-1} H_k^T + R_k \tag{11}$$

where $P_{k|k-1}$ is the predicted estimate covariance derived from (9).

$$K_k = P_{k|k-1} H_k^T S_k^{-1} \tag{12}$$

where S_k^{-1} is the inverse of the innovation covariance computed by (11).

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{\gamma} \tag{13}$$

where $\hat{x}_{k|k-1}$ refers to state estimate in (8), $\tilde{\gamma}$ is the innovation computed by (10) and K_k represents the optimal Kalman gain derived from (12).

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{14}$$

This adaptive process will be continued recursively and the validation of features can be figured out. We can then discriminate the segment with invalid features and the segment with valid features but abnormal morphology.

When the analysis incorporating both of the morphological and the temporal information is completed, we can attain the ensemble assessment of the signal quality which grades the signal segments to four levels. Those segments which are trashed after morphology analysis using metrics I are graded as Level 4. The segments whose features are invalid will be graded as Level 3, while those with valid features and abnormal morphology based on morphology metric I and II analysis will be graded as Level 2. The others which is normal in morphology aspect and have valid extracted features are graded as Level 1. Segments in the last two levels will be rejected and the extracted features of segments in Level 2 will be preserved.

III. EXPERIMENTAL RESULT AND ANALYSIS

The proposed approach was assessed using the data collected from our lab. We conducted an experiment which was approved by the Institutional Review Board (IRB) of our institution using BIOPAC System with 20 healthy volunteer subjects recruited to evaluate the performance of the proposed method. The testing signal is measured from the right forefinger using the reflective TSD200 photoplethysmogram transducer and PPG100C module at the sample frequency 250Hz. Arbitrary movements were required on the right forefinger and right arm while manual annotations about motion artifacts occurrence were taken down during the measurement. All of the data records involved with motion artifacts were evaluated for the performance.

Fig. 3 illustrated the final assessment result which reflected an conjunction of morphological analysis and temporal analysis.

The results of signal quality assessment and the artifacts identification were classified into 3 types: (1) false positive: the valid segment in one period is identified as artifact, which is the case that the signal quality level number assessed by our method is larger than the correct signal quality level number considering our four gradations; (2) false negative: fails to recognize the artifact in one period; the signal quality level number assessed by our method is smaller than the correct signal quality level number considering our four gradations; (3) true positive: the good segment in one period is evaluated as the clean one, which is the case that the signal quality level number assessed by our method is equal

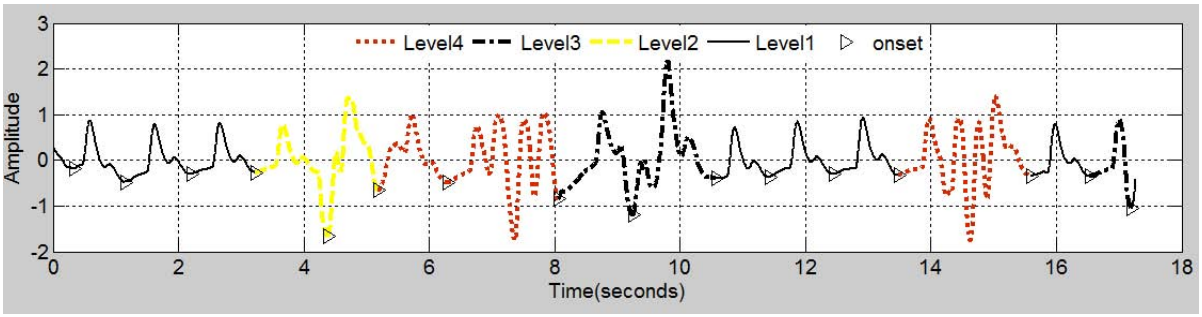

Fig. 3. A Case Study: final assessment result of signal quality

to the correct signal quality level number considering our four gradations.

Literally, compared with morphological-only method and the temporal-only method, our approach can be prominent in identifying the following two cases: a) the extracted features of the segment vary greatly due to the physiological change while the segment is clean actually. These segments may be rejected by temporal-only based method without considering the morphology. b) the extracted features are valid while there exist deformations in the segment to some extent. These segments may be rejected by morphological-only method although the extracted features are useful in fact.

We used the statistical metrics to evaluate the performance of our proposed method. Table I summarized the performance of different signal quality assessment approaches. Our study displayed some preliminary encouraging results in the direction of considering both the morphological and the temporal information for signal quality determination.

TABLE I

SUMMARY OF SIGNAL QUALITY ASSESSMENT RESULTS

Method	L1	L2	L3	L4	TPR	ACC
Manual	50	NA	NA	43	NA	NA
Temporal	69	NA	24	NA	72.46%	79.57%
Morphological	65	NA	NA	28	76.92%	83.87%
MINT	51	11	8	23	98.04%	98.92%

L1: Segments graded as Level 1; L2: Segments graded as Level 2; L3: Segments graded as Level 3; L4: Segments graded as Level 4; TPR: True Positive Rate(Sensitivity); ACC: Accuracy.

IV. CONCLUSIONS AND FUTURE WORKS

PPG sensors is known to be susceptive to motion disturbances and thus will induce false alarm for physiological monitoring. Effective signal quality assessment and intelligently identification of artifacts has a dominant influence on robust vital signs monitoring. Our proposed adaptive signal quality assessment approach not only consider the morphological information but also refers to the temporal variability in the physiological time series and can improve the accuracy of physiological parameter extraction after rejection of artifacts.

In the future, we will apply our algorithm to physiological data in daily life and explore other important features of PPG waveform to distinguish artifacts from pathological change.

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