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Procedia Computer Science 184 (2021) 140–147

Procedia Computer Science

www.elsevier.com/locate/procedia

The 12th International Conference on Ambient Systems, Networks and Technologies (ANT)
March 23 - 26, 2021, Warsaw, Poland

Lightweight Photoplethysmography Quality Assessment for Real-time IoT-based Health Monitoring using Unsupervised Anomaly Detection

Aysan Mahmoudzadeh[a], Iman Azimi[a,*], Amir M. Rahmani[b], Pasi Liljeberg[a]

[a] *Department of Computing, University of Turku, Turku, Finland*
[b] *School of Nursing and Department of Computer Science, University of California Irvine, Irvine, CA, United States*

Abstract

Real-time remote health monitoring is dramatically growing, revolutionizing healthcare delivery and outcome in everyday settings. Such remote services enable monitoring individuals anywhere and anytime, allowing diseases early detection and prevention. Photoplethysmography (PPG) is a non-invasive and convenient technique that enables tracking vital signs such as heart rate, heart rate variability, respiration rate, and blood oxygen saturation. PPG is broadly used in various clinical and commercial wearable devices, as it is easy-to-implement and low-cost. However, the technique is highly susceptible to motion artifacts and environmental noises, which distort the collected signals. Therefore, the signal quality needs to be investigated, and unreliable signals should be discarded. In the literature, rule-based and machine learning-based PPG quality assessment methods have been investigated in several studies. However, the rule-based methods are mostly inaccurate in remote health monitoring, where users engage in different physical activities. The supervised machine learning-based methods –including deep learning– are also infeasible for real-time monitoring applications since they are slow and are dependent on a massive pool of annotated data to train the model. In this paper, we introduce a PPG quality assessment method, enabled by an elliptical envelope, which requires low computational resources. The method clusters the PPG signals into two groups as “reliable” and “unreliable.” We also investigate various features extracted from the PPG signals. Five features with the highest scoring values are selected to be fed to the elliptical envelope model. Moreover, we assess the performance of the proposed method in terms of accuracy and execution time, using data collected in free-living conditions via an Internet-of-Things-based health monitoring system enabled by smart wristbands. The method is evaluated in comparison to a state-of-the-art PPG quality assessment method. We also provide the model implemented in Python for the community to be used in their solutions.

Keywords: Signal quality assessment; Internet of Things; Photoplethysmography; Anomaly detection; Real-time health monitoring

* Corresponding author. Tel.: +358-41-741-5196.
E-mail address: imaazi@utu.fi

10.1016/j.procs.2021.03.025

1. Introduction

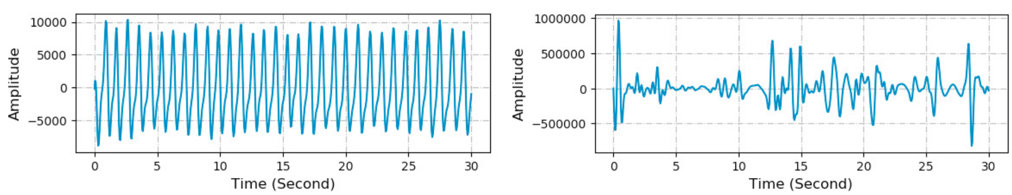
The rapid development of smart wearables and Internet of Things (IoT)-based systems has facilitated remote monitoring of health and well being [4, 3]. Such applications leverage a distinct set of sensing, communication, and computing infrastructures to continuously track individuals' health status and provide real-time decision-making [15]. Wearable devices –such as smartwatches and smart rings– play an important role in this regard, allowing the ubiquitous collection of biomedical signals, including photoplethysmogram [1] and electrocardiogram.

Photoplethysmography (PPG) is a low-cost and convenient optical method capturing synchronous blood volume changes in the microvascular bed of tissues [1]. PPG is conventionally performed, exploiting a light source and a light sensor placed on the finger or wrist. The light with a specific wavelength – which is often red, infrared, or green – is emitted to the skin. Then, the reflection is collected via the light sensor. The collected signals' changes are associated with cardiac oscillation, and hence various health parameters such as heart rate and blood oxygen saturation can be obtained. Due to the simplicity and feasibility of the measurement, the PPG is widely used in various wearable devices and IoT-based applications [14, 2]. The PPG signal is highly sensitive to artifacts generated by the user's motion or environmental noises. The artifacts distort or conceal information within the signal. Figure 1 illustrates samples of reliable and unreliable PPG signals. Unreliable signal could causes incorrect decision-making and misclassification, which is unacceptable for health and well-being applications. Therefore, PPG quality assessment techniques are introduced to prevent misinterpretation by differentiating reliable and noisy signals.

Rule-based techniques have been proposed to investigate PPG signal quality [7, 17, 20]. These techniques extract different statistical features from the peaks and valleys in the signals, including pulse amplitude, width, slope, entropy, power, skewness, and kurtosis. A set of thresholds is then utilized to differentiate heart peaks and false peaks (i.e., noise). For example, Vadrevu and Manikandan [24] proposed hierarchical decision rules to assess the signal quality, using features extracted from the absolute amplitude, zero-crossing rate, and autocorrelation of the signal. Such rule-based techniques are fast and easy-to-implement. However, they might be inaccurate, particularly in remote health monitoring applications, as the users engage in various physical activities, and the noise might be diverse.

Moreover, various studies classify the signal quality as "good" or "bad", exploiting supervised machine learning methods such as K-nearest neighbors and support vector machine (SVM) [17, 18]. These methods extract features from the annotated data and train a classification model. Li and Clifford [13] introduced a dynamic time-warping method to perform template matching. They also used a neural network algorithm to differentiate good and bad quality pulses. Similarly, Chong et al. [7] presented an SVM method, trained by various statistical features extracted from the PPG signals. In addition to the traditional machine learning, deep learning methods were proposed to perform PPG quality assessment. In this regard, Kasaeyan Naeini et al. [16] proposed a convolutional neural network to perform automatic feature extraction of the signal and detect unreliable pulses. Machine learning methods outperform simple rule-based methods, particularly if a large pool of training data is available. However, these methods are mostly suitable for post and batch processing purposed as they are relatively slow and infeasible for real-time monitoring systems. They also need a manual annotation phase since they depend on annotated data to train the models.

Wearable sensors collecting PPG signals require a lightweight real-time PPG quality assessment method with the minimum execution time. It should minimize the need for manual data labeling by an expert, which is time-consuming and expensive. This method should leverage the linear/nonlinear correlations and characteristics of the signals (i.e., similarity of the reliable waveforms) to assess the quality. Moreover, in contrast to the evaluation methods in the



(a) Reliable PPG signals (b) Unreliable PPG signals

Fig. 1: Two thirty-second segments of PPG signals

Table 1: Time domain and frequency domain features collected from the PPG segments

Category	Feature	Description
Time domain	Mean	$\bar{S} = \frac{1}{N}\sum_{i=1}^{N} x_i$
	Median	Middle value separating the signal into two halves
	Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$
	Variation in skewness of the heart cycles	Asymmetry of the heart cycles
	Variation in kurtosis of the heart cycles	Sharpness of the heart cycles
	Variation in energy over the heart cycles	$\text{Max}(\sum_{i=1}^{N} x_i^2)$ - $\text{Min}(\sum_{i=1}^{N} x_i^2)$
	Variation in approximate entropy of the heart cycles	Complexity of the heart cycles
	Shannon entropy	Amount of information of the signal
	Approximate entropy of the signal	Complexity of the signal
Frequency domain	Power of the signal in 12 frequency bands	Power spectral density of the signals between 0.6 Hz and 3 Hz
	Standard deviation of power spectral density	Spread of the power spectral density
	Resonance frequency	Dominant frequency in the power power spectral density
	Spectral entropy	Uncertainty of the spectrum

literature, the method needs to be tested using data collected in free-living conditions, with the presence of artifacts generated from daily routine activities.

In this paper, we propose an unsupervised PPG quality assessment method, exploiting the features extracted from the signal's waveform. This method differentiates "Reliable" signals from "Unreliable" signals that include deformed or noisy peaks. We first investigate various features extracted from the signals and heart cycles. Five features with the highest scoring values for the clustering are selected. We then employ the elliptical envelope as an anomaly detection method to cluster signals into the two groups. Moreover, the proposed method is evaluated in terms of accuracy and execution time compared to a state-of-the-art rule-based PPG quality assessment method. The methods are tested using an IoT-based health monitoring application performed in free-living conditions using wearable devices. We also provide the model implemented in Python for the community to be used in their solutions [1].

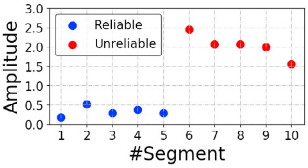
2. PPG Quality Assessment Method

In this section, we thoroughly present the proposed PPG quality assessment, enabled by an unsupervised machine learning method. The data analysis pipeline consists of three main parts. The collected signals are first filtered and divided into segments, within which the noise level is considered as quasistationary. In other words, the segments include "Reliable" or "Unreliable" PPG signals. Second, various features are extracted from the segments, and the similarity of the pulse waveforms is investigated. The "Reliable" segments are expected to include similar pulse waveforms oscillated with the heart cycles. However, the "Unreliable" segments consist of diverse pulses generated from the heart cycles and noises, including motion artifacts and environmental interferences. Considering this characteristic of the PPG signals, we tailor an anomaly detection technique to discriminate between the segments.

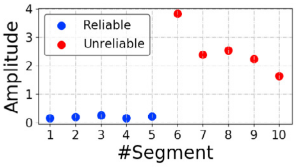
2.1. Pre-processing

We leverage a filtering technique to reject all the frequencies outside the desired (heartbeat) frequency range. In this regard, a Butterworth bandpass filter –with a lower cutoff frequency of 0.6 Hz and a higher cutoff frequency of 3 Hz– is utilized. Therefore, low-frequency (e.g., baseline wandering) and high-frequency artifacts are removed; however, the artifacts within the heartbeat frequency are still available. The filtered PPG signals are nonstationary in terms of the noise level. For the analysis, we divide the signals into (quasi)stationary segments, where the noise level is fixed. The segments are assumed to be "Unreliable" or "Reliable." The length of the segments should be short enough to ensure the noise is stationary but long enough to allow meaningful waveform analysis. It should be noted that too short segments result in low-resolution features. We assume 30-second segments in our analysis.

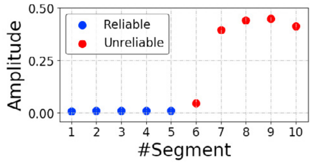
[1] https://gitlab.utu.fi/imaazi/ppg-sqa-ee



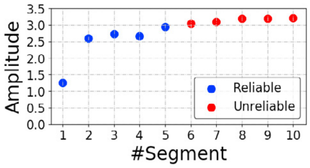
(a) Range of skewness of heart cycles



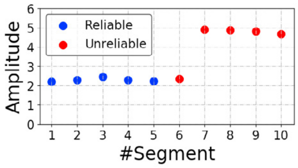
(b) Range of kurtosis of heart cycles



(c) Range of approximate entropy of heart cycles



(d) Shannon entropy of the segment



(e) Spectral entropy of the segment

Fig. 2: Five features extracted from five “Reliable” and five “Unreliable” PPG segments.

2.2. *Feature Extraction and Selection*

The proposed method assesses the PPG signal quality by investigating the variation of the signals within the segments. We extract a wide range of time-domain and frequency-domain features from the segment and from the heart cycles in the segments. The extracted twenty-four features are listed in Table 1. In our analysis, the heart cycles are obtained using a derivative base method. The first derivative of the filtered signal is calculated, and the local maxima and minima are obtained via a threshold. A heart cycle is defined as the signal between two minima, between which are one maximum value (i.e., peak).

Moreover, a univariate feature selection method is utilized to select the features with the highest relationship with the two classes (i.e., “Reliable” and “Unreliable”). In this regard, the analysis of variance (ANOVA) F-value between each feature and the target classes is calculated [12]. Using four-day PPG data, we select the five features with the highest scoring values for the classification. The selected features are variation in the skewness of heart cycles, variation in the kurtosis of heart cycles, variation in the approximate entropy of heart cycles, Shannon entropy of the segment, and spectral entropy. In the following, we outline the definition and implementation of the five features.

2.2.1. *Variation in Skewness of Heart Cycles*

Skewness is conventionally used to measure the asymmetry of a probability distribution. We extract this parameter from the heart cycle to measure the asymmetry of the peak [8, 11]. The skewness of each heart cycle is defined as:

$$S = \frac{1}{N}\sum_{i=1}^{N}[x_i - \frac{\mu_x}{\sigma_x}]^3 \tag{1}$$

where x_i is the heart cycle, N is the number of heart cycle samples, and μ_x and σ_x are the mean and standard deviation of x_i, respectively. Within each segment, the skewness values of the heart cycles are obtained. The range (i.e., maximum value – minimum value) of the skewness is extracted to find the variations between the heart cycles. Figure 2a indicates this feature extracted from five “Reliable” (i.e., blue points) and five “Unreliable” PPG segments (i.e., red point). The difference between the two groups is clearly noticeable.

2.2.2. *Variation in Kurtosis of Heart Cycles*

Kurtosis represents how the tails of a probability distribution differ from a normal distribution. We measure kurtosis of the heart cycles to evaluate its flatness or peakedness level. [22, 8], The kurtosis of each heart cycle is defined as:

$$K = \frac{1}{N}\sum_{i=1}^{N}[x_i - \frac{\mu_x}{\sigma_x}]^4 \tag{2}$$

where x_i is the heart cycle, N is the number of heart cycle samples, and μ_x and σ_x are the mean and standard deviation of x_i, respectively. Similar to the skewness, we calculate the kurtosis of the heart cycles in each segment. Then, the range of the kurtosis values is extracted. As illustrated in Figure 2b, this feature can differentiate the two groups. The variation in the "Reliable" PPG samples are considerably lower than the "Unreliable" samples.

2.2.3. Variation in Approximate Entropy of Heart Cycles

Approximate entropy is a non-linear statistic that quantifies the complexity of the signal [10, 19]. We measures this parameter to determine the complexity of the heart cycles. The approximate entropy of each heart cycle is as follows:

$$ApEn(m, r, L) = \frac{\sum_{i=1}^{L-m} \log C_i^{m+1}(r)}{L-m} - \frac{\sum_{i=1}^{L-m} \log C_i^{m}(r)}{L-m+1} \tag{3}$$

where m is the filter length, r is the tolerance factor, L is the length of the heart cycle, and $C^m(r)$ is the signal correlation, showing the similarity within the signal. For more details see [6]. Figure 2c indicates the feature, obtained from the two groups. The variation of the approximate entropy is relatively higher in "Unreliable" PPG segments.

2.2.4. Shannon Entropy

Shannon entropy indicates the amount of information or uncertainty in a variable. A random white noise signal has the highest Shannon entropy value due to the maximum uncertainty in its pattern. On the other hand, the Shannon entropy of a deterministic signal is small [22]. In this study, we extract the Shannon entropy of the PPG segments to obtain the level of noise in the segment. The Shannon entropy is obtained as:

$$ShE = -\sum_{i=1}^{N} P_i \log(P_i) \tag{4}$$

where P_i is the probability of the segment amplitudes, and N is the length of the segment. The Shannon entropy of the PPG samples are illustrated in Figure 2d. The "Reliable" samples have relatively lower values.

2.2.5. Spectral Entropy

Spectral entropy is an appropriate feature to calculate the signal complexity in the frequency spectrum. A reliable PPG signal with a high amplitude of resonance frequency has low spectral entropy. However, a noisy PPG signal with uniform power spectral density (PSD) has higher spectral entropy. In our analysis, we calculate the spectral entropy of the PPG segments, as follows:

$$SE = -\sum_{f=0}^{f_s/2} P(f) \log_2[P(f)] \tag{5}$$

where P is the probability of normalized amplitude of the PSD, and f_s is the sampling frequency. Figure 2e indicates the spectral entropy of 10 PPG samples. Similar to the other entropy values, the "Reliable" samples have lower values.

2.3. Anomaly detection

Anomaly detection is the process of identifying outliers that are different from the expected patterns or trends in the data [5]. There is a large body of literature on anomaly detection techniques employed in various applications [5]. These techniques are designed according to the type of data, the type of anomalies, and the labeled data's availability. Supervised anomaly detection techniques construct a predictive hypothesis function to distinguish abnormal behavior. However, these methods are dependent on annotated data for the expected pattern and outlier classes. The availability of annotated data is a challenge for many applications, particularly long-term health monitoring, as the data labeling by an expert is expensive and time-consuming.

In contrast, unsupervised anomaly detection techniques address outlier detection in unlabeled data. These techniques assume that 1) normal instances occur more often than outliers, and 2) normal instances are in dense clusters, but outliers are sparse [5]. With this intention, we leverage an unsupervised anomaly detection method to differentiate the PPG signals. In these signals, "Reliable" segments are repetitive with uniform waveform, oscillated with heartbeats. On the other hand, "Unreliable" segments are diverse due to the additive (random) noise.

Fig. 3: A view of the elliptic envelope method

The elliptical envelope algorithm is an unsupervised anomaly detection method, detecting outliers based on a multivariate Gaussian distribution obtained from the covariances between the features [23]. The algorithm assumes that the features have Gaussian distribution and defines an ellipse to distinguish the outliers. The normal samples are close to the mean value, while the outliers are far from the centroid. Figure 3 shows a view of the method, where the normal samples (green dots) with high density are in the ellipse. However, the samples in the low-density regions are specified as outliers (red dots). The size and the shape of the ellipse are estimated via a contamination parameter based on the Fast Minimum Covariance Determinant method [21]. The method obtains the Mahalanobis distance between the samples and the Gaussian distribution. The Mahalanobis distance is calculated as follows:

$$d^2 = (x_i - \mu)^T C(x_i - \mu) \tag{6}$$

where x_i is the sample, μ is the mean value, and C is the covariance [9].

3. Experimental Results

The proposed method is evaluated in terms of accuracy and execution time, using a proof-of-concept IoT-based healthcare application. In the following, we first outline the data collection setup. We briefly describe a rule-based PPG quality assessment method, with which our method is compared. Then, the comparison results are presented.

3.1. Data Collection Setup

In our setup, the PPG signals were measured using the Samsung Gear Sport watch, which runs an open-source Tizen operating system, allowing us to develop our data collection application. The watch is lightweight and waterproof, including adequate amount of internal memory for long-term data collection. It also consists of built-in optical sensor to capture green PPG signals with a sampling frequency of 20 Hz.

The data collection was performed for six days in free-living conditions. The participants were asked to wear the device on the non-dominant hand and to engage in their daily routines during the monitoring. Due to the limited battery, we programmed the watch to measure the PPG signals for 12 minutes every second hour. As a proof of concept, we evaluate the proposed method using the data of five (female) healthy individuals with the average age of 35.2 ± 5.3 years. We first manually annotate the data as “Reliable” and “Unreliable.” Then, we compare the true labels with the results of the proposed method and the baseline method. The methods were implemented in Python.

Ethics: The study was conducted according to the ethical principles based on the Declaration of Helsinki and the Finnish Medical Research Act (No 488/1999). The study protocol received a favorable statement from the ethics committee (Unversity of Turku, Ethics committee for Human Sciences, Statement no: 44/2019). The participants were informed about the study, both orally and in writing, before their consent was obtained. Participation was voluntary, and all the participants had the right to withdraw from the study at any time and without giving any reason.

3.2. The Baseline PPG Quality Assessment Method

We evaluate the proposed method’s accuracy and execution time, compared to a rule-based PPG quality assessment method [24] as a baseline. The baseline method is implemented and tested with the collected data. In this method, low-frequency noise is removed via a Butterworth high-pass filter. Then, the PPG signals are classified into “Reliable” and “Unreliable” using six hierarchical decision rules. Two rules are related to the amplitude of the PPG signal, two rules are obtained using the zero-crossing rate, and the last two rules are defined based on the autocorrelation function of the windowed PPG signals (see more details in [24]).

3.3. Accuracy Assessment

We evaluate the accuracy of the proposed method using the data collected from five individuals via the Samsung watch. The unsupervised proposed method divides the data into two clusters. To evaluate this division, we cross-validate the performance of the proposed method by implementing intra-participant and Inter-participant tests. For the intra-participant test, the training and testing data are collected from the same participants at different time intervals. In contrast, the training and testing data of the inter-participant test are collected from separate individuals.

3.3.1. Intra-participant Test

We compare the performance of the proposed method with the baseline method via the intra-participant test. The proposed method is trained using the four days of data from one individual. Then, the methods are tested via the PPG signals collected from the two following days. The normalized confusion matrices of the baseline method and proposed method (intra-participant) are indicated in Table 2. In addition, Table 3 shows the precision, recall, F1-score, and support values. The results show that the proposed method is slightly better than the baseline method to detect "Reliable" signals. However, the proposed method significantly outperforms the baseline method in "Unreliable" sample detection. In other words, the proposed method is obtained a considerable lower false-negative rate. Remote health monitoring necessities such a low false-negative rate, since the motion artifacts (i.e., outliers) are prevalent.

3.3.2. Inter-participant test

The proposed method is evaluated via the inter-participant test. In this regard, the method is trained using six days of data from four participants. Then, the testing phase includes the six-day data of one individual. The results are indicated in Table 2 and Table 3. In both inter-participant and intra-participant tests, the "Unreliable" samples detection (i.e., true negative) is almost similar. In contrast, the method achieves worse performance in the inter-participant test to detect the "Reliable" samples (i.e., true positive). The method's performance in the intra-participant test is higher since the model is personalized by seeing similar samples from the same user in the training phase.

3.4. Execution Time Assessment

We assess and compare our method's execution time (i.e., a critical metric in real-time health monitoring) against the baseline method. We measure the execution time of the proposed method –including pre-processing, feature extraction, and anomaly detection– and the execution time of the baseline method –including the six decision rules. The test is performed in Python on a personal computer with a 6-core Intel Core i9 CPU at 2.90 GHz and 32GB RAM.

The proposed method's latency to cluster a segment is 12.75 ± 0.60 ms, and the baseline methods' latency is 2.75 ± 0.47 ms. The baseline method has less execution time; however, the delay for both methods is insignificant in comparison to other existing methods in the literature [24, 20] whose execution time ranges from 80 ms to 600 ms (i.e., 1-2 orders of magnitude higher). Our future work considers execution time assessment of the proposed method on wearables by comparing the method against other rule-based and machine learning-based methods.

Table 2: Normalized confusion matrices of the baseline method and proposed method (intra-participant and inter-participant tests)

Method		Predicted: R*	Predicted: U
Baseline	True: R	0.94	0.06
	True: U	0.36	0.64
Proposed (intra-participant)	True: R	0.95	0.05
	True: U	0.03	0.97
Proposed (inter-participant)	True: R	0.89	0.11
	True: U	0.02	0.98

* R is "Reliable," and U is "Unreliable."

Table 3: Precision, recall, F1-score, and support of the the baseline method and proposed method (intra-participant and inter-participant tests)

Method	Label	precision	recall	F1-score	support
Baseline	R*	0.93	0.94	0.93	826
	U	0.69	0.64	0.66	174
Proposed (intra-participant)	R	0.98	0.95	0.97	553
	U	0.95	0.97	0.96	503
Proposed (inter-participant)	R	0.99	0.89	0.93	1733
	U	0.85	0.98	0.91	1147

* R is "Reliable," and U is "Unreliable."

4. Conclusion

PPG signals collected via wearable sensors are highly sensitive to artifacts generated by the user's motions. Such artifacts distort the signals, leading to inaccurate decision-making. Conventional quality assessment methods are inaccurate or infeasible for remote health monitoring, where the signal quality should be assessed instantaneously. This paper proposed a lightweight PPG quality assessment method to differentiate valid and noisy PPG signals collected from wearable devices. We first investigated twenty-four features extracted from the signal and selected five features with the highest scoring values. We then exploited the elliptical envelope method –as unsupervised anomaly detection– to cluster the signals into the "Reliable" and "Unreliable" groups. The method was evaluated using six-day PPG data acquired via wearables in free-living conditions. The method was compared to an existing rule-based method. Our results showed that the proposed method outperforms the baseline method, particularly in unreliable signal detection. In our test, the unreliable signal detection improved (e.g., F1-score by 5%) through personalization: i.e., using the same user's data in the training phase. We also indicated that the proposed method latency is slightly higher than the baseline method but is small compared to other methods in the literature. In future work, we implement the proposed method in wearables and evaluate the delay in comparison to other rule-based and machine learning-based methods.

Acknowledgement

This work was supported in part by the Academy of Finland under Grant 316810 and Grant 316811 (SLIM Project) and in part by the U.S. National Science Foundation under Grant SCC CNS-1831918 (UNITE Project).

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