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Investigation of Cardiac Abnormalities with ECG Signal Analysis: A Review Work

Uday Maji

Dept. of Applied Electronics and Instrumentation Engineering

Haldia Institute of Technology

Haldia

Abstract: Abnormal electrical activities in the heart cause various types of arrhythmia or cardiac dysrhythmia. Atrial fibrillation and atrial flutter are most important among them. Various methodologies have been used for the automatic detection of this arrhythmia for last two decades. In this paper we review most of the technique that have been successfully applied to detect this dysrhythmia. Finally a comparative analysis, based on the used methods and performance parameter is done. In this comparative study includes type of arrhythmia consider, number of lead used, type of signal i.e. ECG, BCG, EEG or other, and analysis based on the features and classification technique. The comparative study includes the cases where training and testing data come from the same and different sessions (days). The results show that most of the algorithms that have been proposed for atrial arrhythmia diagnosis perform well when the training and testing data come from the same session.

Introduction: Heart beats are generated from Sino-atrial (SA) node, then the wave spreads to the atrioventicular (AV) node and then down the His bundle to the ventricles. The conduction of this pulse can be delayed or blocked at any point which results in abnormalities in the rhythm. Abnormal rhythm may be arising at the atrial muscle, junction region or the ventricular muscle. In this paper abnormality related to atria called, atrial arrhythmia is of interest. Atrial arrhythmia may be Premature Atrial Contractions (PAC), Wandering Atrial Pacemaker, Multifocal atrial tachycardia, Atrial Flutter (AFL) and Atrial Fibrillation (AF) [1].

Premature atrial contraction or atrial premature beats is premature heart beat originate when other than SA node trigger the heartbeat. It may be seen in young and elder people without hear diseases. Sometime it causes sensation of palpitation. It is mainly appear on ECG signal as the abnormal shape of the P-wave.In normal case it do not show any health risk but for the person with structural heart problem it can cause other arrhythmia like atrial flutter or atrial fibrillation and for the other cases PAC beat disappears automatically.

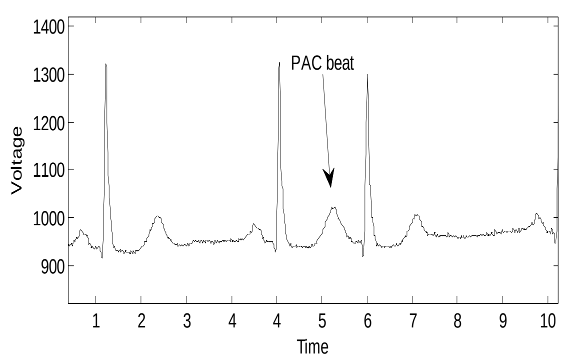

Fig.1 Premature atrial contraction beat

Atrial fibrillation is the most common arrhythmia increases the risk of heart attack. It is caused by the irregular conduction of impulses to the ventricles. AF may stands for a minute or a day long. More risk may be caused by the AF are cardiovascular and metabolic comorbidities like hypertension, coronary artery disease, congestive heart failure, and myocardial infarction [2, 3]. Atrial fibrillation is characterized by the irregularity of RR intervals (RRI) and the fibrillatory electrical Atrial Activity (AA). Electrical atrial activity is characterized by the absence of P-wave and special frequency properties [4]. Identification of AFsis mostly done by the researcher based on the property, irregularity of RR interval and some work has done based on absence of P-wave.

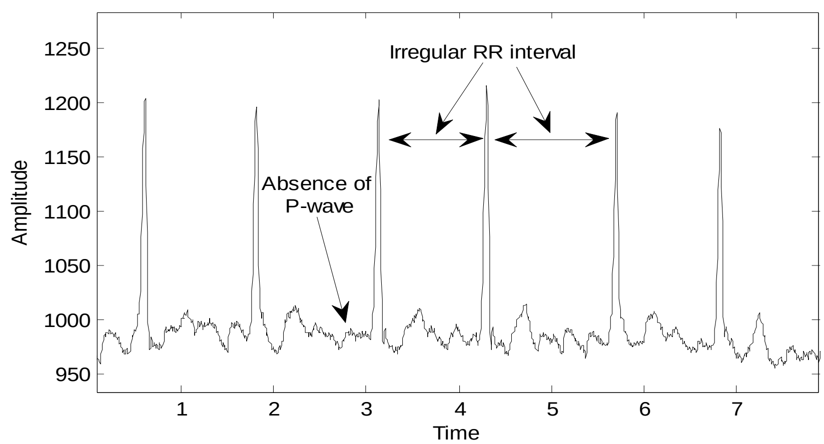

Fig2. Atrial Fibrillation Wave.

Atrial flutter (AFL) is usually associated with fast heart rate and falls into the category of super ventricular tachycardia. It is characterized by the flutter wave at a rate of 250 to 400 beats per minute. Flutter wave may be of symmetrical, resembling to P-wave or may be asymmetrical of saw-tooth shape.Atrial-ventricular rhythm present in the AFL wave may be in the ratio of 1:1, 2:1 or 4:1 [5]. Atrial flutter can be overcome automatically but the people with other heart disease may gain the symptoms like shortness of breath, chest pain, dizziness etc.

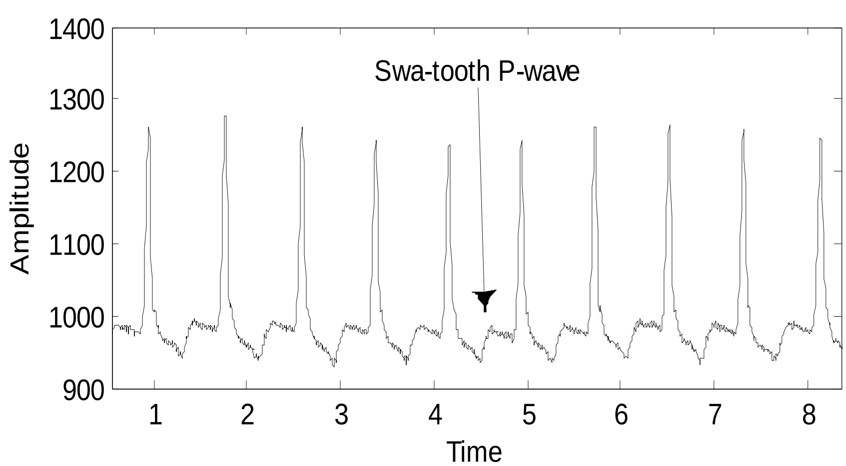

Fig3. Atrial flutter wave

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Accurate detection of the all arrhythmiais very important to provide the proper medical treatment. Among all the arrhythmia discussed above atrial fibrillation and atrial flutter are the most important, because it can cause serious life threatening heart dieses. For the automatic detection of the flutter and fibrillation wave various works have been done for the last two decade. Detections are based on the various properties of the fibrillatory waves and classifications have been done either in time domain or in frequency domain, such as Time-Varying Coherence Function, Support Vector Machine (SVM), wavelet decomposition, Shannon Entropy, Empirical Mode Distribution (EMD) and statistical parameter.

In this review paper we summaries all the existing method present in the literature on detection and classification of different fibrillatory wave based on the ECG. A detection system basically operates in two modes, in training mode or in testing mode. In training mode the system has been trained or prepared with input data. In testing mode input data are classified as whether it is an arrhythmia or not. If any input data is wrongly rejected, the system is said to have earned a false rejection error and when it is wrongly accepted, it is called a false acceptance error occurs. Performance of each technique is measured in terms of specificity, sensitivity and accuracy.

The classification technique of AFL and AF may group together, based on number of ECG data channel used, position of the electrode placed on the body, method of detection and the domain of analysis whether time or frequency.

Most the analysis on arrhythmia is done with the signal channel ECG signal, but Marianna Meo et al. [6] use 12-Lead Surface ECG to analysis heart electrical activity from different spatial locations. Leads I, II, III, V1 and V2 are used for Atrial signal analysis in the literature [17]. I Christov et al [25] tested their algorithm for all the 12 leads as well. Other than ECG signal Jinseok Lee et al [7] collected 2-min pulsatile time series by using an iPhone 4S, and ChristophBruser et al [8] used cardiac vibration signals (ballistocardiograms/BCGs) recorded by unobtrusive bed mounted sensors for the analysis of AF and AFL signal. Martin Stridh et al [9] use the thumb ECG for the repeated measurement of AF at home. Other than ECG work has been also done based on the EndocardialElectrograms by P Rossi et al [10], and Richard P. M. Houben et al [20].

Different process and parameter has been used to extract the feature from the flutter or fibrillatory wave of standard data base. These features are used to detect the arrhythmia automatically. But it is also important to identify the transition of normal sinus rhythm to abnormal rhythm or vice-versa. Point of transition from AF to AFL rhythm or vice-versa is also very important. Ronan Lepage et al [11] and SalimGraja et al [12] have been used segmented P-wave to detect the patient prone to atrial fibrillation.Classification between terminating AF and non-terminating AF has done by B Logan et al [13] and LT Mainardi et al [14] and termination moment of AF is also detected based on RR interval [27] variability and increase of Approximated Entropy.

Rest of the paper is organized as, survey of different methods based on the segmented or non-segmented ECG signal and classification technique. Next section consists of a comparative study of result proposed in various researches. In the last section a new algorithm is proposed for the AF detection.

Survey of AF and AFL recognition methods: There are so many feature extraction and reduction techniques that have been proposed for use in detection of AF and AFL rhythm. Moreover different types of classifier have been utilized for placing test feature vectors into predefined classes. In this paper work is group together depending on the feature extraction method and classifier.

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Algorithm based on fiducial features: Algorithm based on the fiducial feature for the detection of AF and AFL uses characteristic points, such as- wave peaks, onset, offset obtained from the ECG. For example R peak of the wave is a characteristic point while interval between two R peaksor R and T are the fiducial feature. As the R to R time interval in case of AF is irregular and for AFL interval is very small, this fiducial feature is used by most of the researcher-[6], [7], [15], [16], [17], [18].

Algorithm based on non-fiducial features: Algorithm based on non fiducial feature do not use characteristic point for feature extraction rather it use more than on characteristic point for heart beat segmentation or it may use a segment of ECG signal.Sometimethis method requires detection of R-peak for heartbeat segmentation and alignment. Work based on this feature suggested in the literature [8], [12], and [20].

Categorization based on the feature and Classifier: Detection of AF and AFL can be group together based on the type of classifier and feature vector are used in the various research. A classic linear classificationtechnique is discussed in [11], which is applied on the parameter like lengthening of the P-wave duration and ratio of spectral power contained in the 20-50 Hz band and in the 0-20 Hz. A nonlinear feed forward neural network with single hidden layer is discussed in [14], [23]. In this work feature vectorcomprises linear index obtain from spectral analysis and nonlinearparameter based on entropy measurement. Spectral analysis mainly consists of frequency (fibrillatory rate), amplitude, total spectral power and spectral width. Nonlinear parameters include regularity and synchronization. Feature from the RR interval such as mean, Standard deviation and Root mean square standard deviation (RMSSD), level of predictability and the nonlinear parameter like Approximated Entropy are also used.

Statistical parameter RMSSD, the Shannon entropy (ShE) and the sample entropy (SampE) are used in [7] as well. Here RMSSD/mean value is calculated on down sampled signal. It shows the value of RMSSD/mean and ShEof AF is very high and completely distinct from NSR. Similarly a value of SampEindicates low similarity in the time series and vice-versa.

Most important feature irregular RR interval is also used in the literature [15]. Here for the measurement of scatter plot is fitted in an ellipse and the length and width is measured as SD1 (the standard deviation of the distances of points from y = x axis) and SD2 (standard deviation of the distances of points from y=x+2RR axis, where RR is the mean of all the R-R intervals) of the ellipse. The value of SD1 and SD2 indicates short-term variability and long-term variability respectively. It also uses the parameter like Vector Angular Index (mean of all the absolute value of angular differences between the lines plotted from every scatter point to the original point and the diagonal line) and Vector Length Index (standard deviation of all distances of scatter points from the original point). Finally ROC (Receiver Operating Characteristic) curve which is a two dimensional description of classifier, used to calculate the sensitivity and specificity of the algorithm. ROC curve is also used in by S Dash et al [16] to measure the performance by calculating the area under the curve. In this paper AF and AFL both rhythm have been classified based on the statistical and time-frequency parameter. AF rhythms have been identified depending on the statistical parameter value RMSSD, turning point ratio (TPR) and Shannon entropy. An AND condition i.e. if all the parameter crosses their respective thresh hold valuethe segment is considered as AF. Similarly AFL rhythm has been detected by using time-frequency method. Here time-frequency spectrum (TFS) is obtained by using variable frequency complex demodulation method (VFCDM). If peak frequencies (frequency of highest spectral peak of TFS) greater than a certain threshold frequency it consider the RR interval as Type-I flutter.

Support vector machine (SVM) has been used as classifier in the work [12], to identify the patient prone to atrial fibrillation. Four type of parameter were selected for this classifier. Two of them are P-wave duration and shape of P-wave (symmetrically shaped P-waves, slowly descending values P-waves, slowly ascending values P-waves, bimodal P-waves and diphasic P-waves). It is also introduce a parameter by coupling this two as shape-duration to discriminate the same duration P-wave with different shape. Other two are spectral parameter (obtained by Morlet continuous wavelet analysis) and wavelet entropy parameter.

For the screening of AF obtain from thumb ECG, rhythm analysis [9] has been done with help of various parameter like standard deviation of RR series (RRstd), the percentage of RR intervals within an interval of ±60ms around the median value (RRpm60), frequently occurring bigemini rhythms in filtered versions of the RR series, the number of separated groups of RR intervals. In addition of this for the detection of P-wave parameter used are PAVB (ratio of main peak in the P wave interval and the noise level in the entire average beat), PAME (P wave average model error), PACC (the part of the concatenated P wave signal having a low enough model error making it acceptable for clustering), PCLU (the percentage of signal blocks represented by the largest waveform cluster), and PSTR (the strength of the largest waveform cluster). Finally rhythm shorting is done by using this parameter. It is classified into the groups- series not accepted (UNACC), Low priority (LOW) containing regular rhythms, or High priority (HIGH) containing irregular rhythms. AF rhythms are mainly fall within the high priority group.

A decision tree classifier has been discussed by Eric Helfenbein et al [17] to characterize the AF beat in presence of paced rhythm. In this literature residue of QRST segment is considered for frequency domain analysis. Here features from the power spectrum and irregularity of non-paced beats are used for the classification. Paced beats are identified by distinguishing between regularly paced rhythm and non-paced beat.For classification of AF rhythm auto correlation function (ACF) and power spectral density have been calculated.

Atrial Flutter rhythm diagnosis has been done by C Brohet et al [21] with the help of discrete wavelet transform (DWT). DWT has been applied on QRS reduced segment and real part at the two frequencies 5 and 10Hz computed. Thirteen discriminant criteria such as the mean heart rate and its variance, and measurements on the 5 and l0Hz DTW, e.g., the ratio of the number of peaks, the mean amplitude of the peaks, the maximal peak at 5Hz, etc. are applied in a particular sequence to qualify eachECG as "Flutter", "Possible flutter" or "Non Flutter".

Tran Thong et al [18] propose a technique for the detection of onset period of proximal atrial fibrillation (APF) by using three criteria: the number of premature atrial complexes (PAC) not followed by a regular R-R interval, runs of atrial bigeminy and trigeminy, and the length of any short run of paroxysmal atrial tachycardia. Any increase in activity is detected by these criterions.

Decomposition of the ECG in a set of coefficients with different temporal and spectral features by means of Discrete Packet Wavelet Transform (DPWT) facilitated to study about atrial activity AF and AFL [22]. Classification of AF by using fuzzy classifier has been proposed by Francisco Rinc´on et al [19]. This research has been performed on ECG signal obtained from Wireless Body Sensor Network (WBSN). Here variation of heart rate and correlation coefficient of between the P wave detected by the delineation algorithm and predefined P wave model is provided as the feature vector to the fuzzy classifier.

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Sequential analysis for characterizing the AF and AFL rhythm is done by I Christov et al [24], based on the testing of P-wave, arrhythmia, and atrial activity.

A new algorithm of coupling genetic programming with orthogonal least squares (GP/OLS) and simulated annealing (GP/SA) [25] has been applied to the classifyatrial fibrillation (AF) episodes from normal sinus rhythm. In this work a radial basis function (RBF) neural networks-based model further used to benchmark the GP/OLS algorithm. Performance of GP/OLS and GP/SA classifiers has been measured by ROC analysis.

Multiple classifiers are used by ChristophBr¨user et al [8] on BCG data considering several feature vectors. Seven different classifiers have been considered and performance measured based on the speed and simplicity of the algorithm. Algorithms used are Naive Bayes (NB), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM), Bagged Trees (BaT), Random Forests (RFs) and Boosted Trees (BoT). To provide the potential input for the classifier both time domain (standard deviation, kurtosis, skewness and peak to peak amplitude) and the time-frequency domain (power spectral density) features are computed. An Autoregressive (AR) method is used to estimate the power spectral density (PSD) slices. Statistical parameters are computed on PSD in order to quantify whether or not spectral line present. K nearest neighbors (KNN), Bayes optimal classifier and artificial neural network (ANN) classifier have been used by B.Pourbabaee et al [26] and compared their performance for paroxysmal atrial fibrillation rhythm.

Indication of onset or offset moment is similarly important like AF detection. Chao Huang et al [27] have been proposed a methodology for onset detection with the help of irregularity of RR interval. Irregularity of RR interval has been measured by using delta RR interval distribution difference curve (dRDDC). Classification of AF event is done from the histogram plot analysis, standard deviation analysis, number of aberrant rhythms recognition and Kolmogorov–Smirnov test.

U Maji et al [28] has been used a linear classifier known as decision function for the separation of AF rhythm from NSR. It uses EMD technique for the feature extraction from the segmented ECG signal.

COMPARATIVE ANALYSES AND RESULTS

Characterization and detection of flutter and fibrillation wave has been going on since 1994. It is observed that most of the feature has been derived for the classification based on the irregularity of RR interval. It is also observed that among all the atrial arrhythmia most of the work has done on atrial fibrillation and some on atrial flutter [16], [21], [24], [29].In this research AF and AFL rhythm are characterized separately but I Christov [24] only categorizes the either NSR or AF/AFL rhythm. In the work [29] it is developed a non-invasive technique to quantitatively characterize the differences between atrial fibrillation and flutter. Whereas in literature [16] time domain and frequency domain analysis has been separately studied to identify the AF and AFL respectively. They have also applied their algorithm on different data base as well.

Research based on the transition period of AF is also pointed in [11], [12],[13], [14],[27]. Among this work in [27] both the onset and offset time based on the dRDDC (delta RR interval distribution difference curve).In the work [11] and [12] a P-wave segmentation method applied to an automatic classification of people prone to atrial fibrillation. In another work [13] and [14] have presented approaches to distinguish various types of terminating and non-terminating and spontaneous terminating AF respectively.

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The results presented here were obtained based on implementing the methodologies as described in the literature. The within-session analysis results are given in Table I, which shows each algorithm, the classification performance reported in the paper, and its performance using standard database.

STUDY	SampleSize	Feature and Technique	RT	CT	ACC	Se	SP
Jinseok Lee et al.[7]	-	RMSSD, SE, SampE, TVCF	AF+NSR	Comparison of feature vectors with threshold	97.49 %	97.41 %	97.54 %
ChristophBruser et al.[8]	30s BCG	Statistical parameter + PSD	AF	NB, LDA, QDA, SVM, BaT, RFs, BoT	96.1	93.8%	98.2%
Martin Stridh et al. [9]	30s	Statistical parameter	AF	Based on parameter value	>65%		-
P. Rossi et al. [10]	0.5 to 20 sec	EMA	NSR+ AF	Comparison of threshold value	-	90%	96%
Ronan Lepage et al [11]	-	HMM	AF	Wavelet analysis		65%	70%
SalimGraja et al [12]	1min	Time and shape	AF	SVM		90%	87.5%
B Logan et al [13]	10s	Statistical parameter	AF	Based on parameter value and ROC		96%	89%
LT Mainardi [14]		Statistical parameter and PSD		NN	-	-	-
XiuhuaRuan et al [15]	60secs	CWT+Scatterplot+VAI +VLI	AF	ROC curve	-	100%	100%
S dash et al[16]	128 beats	RMSSD, TPR, SE, T-F Based method	AF+AFL	-ROC	-	97%	95%
Eric Helfen-bein et al.[17]	-	DXLalgorithm	AF + Paced	Decision Tree Classifier	-	71%	97%
Tran Thong et al.[18]	30 min-	feature from RR series	AF	PAC test, Global bigeminy test, Local bigeminytest, end of	84	89%	91%

				record test, PAT test			
Francisco Rincon et al.[19]	10 s	Wavelet	AF	Fuzzy Classifier	-	96%	93%
R. Couceiro et al. [23]	12secs	KL+FFT	AF	ANN	-	93.8%	96.09 %
I Christov et al.[24]	8s	Statistical parameter	AF+AFL	-	98.8	95.7%	98.3
B. Pourbabaee et al.[26]	30 mins	Statistical parameter, PSD	AF	KNN, BOC, ANN	>75%	-	-
Chao Huang [27]	-	dRDDC,	AF+NSR	HA, SDA, NAR, K-S test	-	96.1	98.1
BF Giraldo et al.[29]	2 sec	Statistical parameter	AF+ AFL	-	-	90%	-
M. Milisavjevic et al.[30]	10s	Cycle length and amplitude	AF	Discriminating function	-	90%	96%
K Tateno [31] et al.		KS algorithm and standard density histograms	AF	Comparison between KS algorithm and standard density histograms value	-	93.2%	96.7%

TECH=Techniques, RT=Rhythm Type, CT=Classifier Type, ACC=Accuracy, SE=Sensitivity, SP=Specificity

Indices stand for: AF=Atrial Fibrillation,NSR=Normal sinus rhythm, AFL=Atrial Flutter, CWT=Continuous Wavelet Transform, VAI=Vector Angular Index, VLI=Vector Length Index, KL= Kullback–Leibler divergence, BCG =ballistocardiography, EMA=Electrogram Morphology Algorithm, KS= Kolmogorov-Smirnov Test,Prob= Probabilistic Distributions,ANN=Artificial Neural Network,RMMSD=Root Mean Square of standard Deviation, SE=Shannon Entropy,SampE=Sample Entropy,HA=Histogram Analysis, SDA=Standard Deviation Analysis, NAR= Numbering Aberrant Rhythms, PSD= Power Spectral DEnsity, TPR= Turning Point Ratio, AA=Atrial Activity,KNN= K Nearest Neighbour, LDA=Linear Discriminant Analysis, ED= Empirical Detector,BOC= Bayes Optimal Classifier, NB=Naïve Bayes, QDA=Quadratic Discriminant Analysis, SVM= Support Vector Machine,BaT=bagged Trees, RFs=random Forests, BoT=Booted trees. PAF= Paroxysmal atrial Fibrillation, TVCF= Time-Varying Coherence Function, dRDDC= RR interval distribution difference curveHMM=Hidden Markov Models

It is being observed that most of the works do not use any established classifier for the identification of arrhythmia. These analyses are mainly characterized by the statistical parameters which are being compared against some threshold value. This threshold values are derived from the analysis of normal rhythm. From the table it is observed that literature [15] shows the highest sensitivity and specificity. But in this method different threshold value has been used for different parameter as well as for betterment of result. This threshold values may be of place dependent as well.

Methodology uses for transition detection of AF rhythm, [27] shows best result among all the proposed technique. In this work multiple algorithms have been used for AF transition detection and their

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performance compared. This method has applied on two different data base as well.Work proposed in [13] also shows a good result. But for this work only feature from the variation of RR interval has consider. In the literature [14], atrial fibrillation episodes have been investigatedto identifythe signs of spontaneous termination of rhythm. From this feature a classifier has been designed to indicate whether a AF episode is terminating or nonterminating.

Conclusion

Almost all the existing methods require exact detection of fiducial points of ECG signal for accurate classification. But as per the reported works no feature extraction technique can claim 100% accuracy for all kind of rhythms. So requirement of minimal features may lead to better classification accuracy. In view of this, it is proposed a work on region based analysis using modern signal processing tools which leads to better accuracy of detection.

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