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saccade detection,
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FUZZY CLUSTERING BASED METHODS FOR NYSTAGMUS MOVEMENTS DETECTION IN ELECTRONYSTAGMOGRAPHY SIGNAL

The analysis of optokinetic nystagmus (OKN) provides valuable information about the condition of human vision system. One of the phenomena that is used in the medical diagnosis is optokinetic nystagmus. Nystagmus are voluntary or involuntarily eye movements being a response to a stimuli which activate the optokinetic systems. The electronystagmography (ENG) signal corresponding to the nystagmus has a form of a saw tooth waveform with fast components related to saccades. The accurate detection of the saccades in the ENG signal is the base for the further estimation of the nystagmus characteristic. The proposed algorithm is based on the proper filtering of the ENG signal providing a waveform with amplitude peaks corresponding the fast eyes rotation. The correct recognition of the local maxima of the signal is obtained by the means of fuzzy c-means clustering (FCM). The paper presents three variants of saccades detection algorithm based on the FCM. The performance of the procedures was investigated using the artificial as well as the real optokinetic nystagmus cycles. The proposed method provides high detection sensitivity and allows for the automatic and precise determination of the saccades location in the preprocessed ENG signal.

1. INTRODUCTION

Nystagmus is a type of eye movement produced as a response to stimuli which activate the vestibular and/or the optokinetic systems [13]. There are two types of nystagmus movements distinguished: congenital (CGN) and optokinetic (OKN). CGN is characterized by involuntary, conjugated, bilateral to and from ocular oscillations that result in degrade of the vision. OKN is a involuntary eye movement response when moving stimulus in a large visual field is presented [15]. Optokinetic nystagmus is frequently used in the diagnosis of the oculomotor system condition, which primary function is to keep the image of the surrounding world stationary with respect to retina whatever the dynamic conditions of the body [1]. The assessment of the oculomotor performance is very helpful in diagnosing of the human visual system. The oculomotor evaluation may be performed on the basis of the electronystagmography signal analysis as the cornea-retinal potential creates an electrical field in the front of head [14].

In studies on the OKN phenomena electronystagmography (ENG) is frequently used. The signal is recorded by placing electrodes around eye. Consequently, it is possible to obtain independent recordings of each eye movement activity separately. The amplitude varies in the range from about 50 μV to 3500 μV and frequency from about DC to 100 Hz. A saw tooth waveform is the characteristic shape of the ENG signal for each type of nystagmus. The slope on one side of each peak is smaller (slow component) that on the other side (fast component). These fast components are called saccades [7]. The

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slow component of the nystagmus is related to the stimulus while the saccade refers to a rapid reset of eye position by the oculomotor systems [5].

The accurate detection of saccades in the OKN cycles is necessary when determining the nystagmus characteristic. The simplest way to detect saccades in the ENG signal is based on comparing the resulting rectified velocity waveform to a fixed threshold. If the signal exceeds the assumed threshold, then it is concluded that a saccade occurred [8]. However, better results can be obtained with the analysis of the eye movement acceleration signal combined with the adaptive-threshold model [2]. The paper presents the saccades detection method based on Savitzky-Golay filtering [8] with the adaptive amplitude thresholding for the detection function (velocity signal) using fuzzy clustering. Three variants of the saccades detection procedure based on the Fuzzy c-Means [4] algorithm are proposed allowing for the precise determination of saccades location in the preprocessed ENG signal.

2. THE METHOD OF SACCADES DETECTION

The correct location of saccades in the ENG signal $(x\,(n))$ is difficult due to the presence of noise, which main source is an electrical activity of eye's and face's muscles. Therefore, in the first stage of the saccades detection the $x\,(n)$ is filtered and the signal features that are useful in positioning of saccades are enhanced. With the proper structure of the filter banks (Fig. 1) we get a normalized signal $y_n\,(n)$, which local peaks correspond to the dynamic change of the ENG signal being the result of fast saccadic eyes movements. Figure 2 shows an example of ENG signal corrupted with noise and the corresponding $y_n\,(n)$ signal.

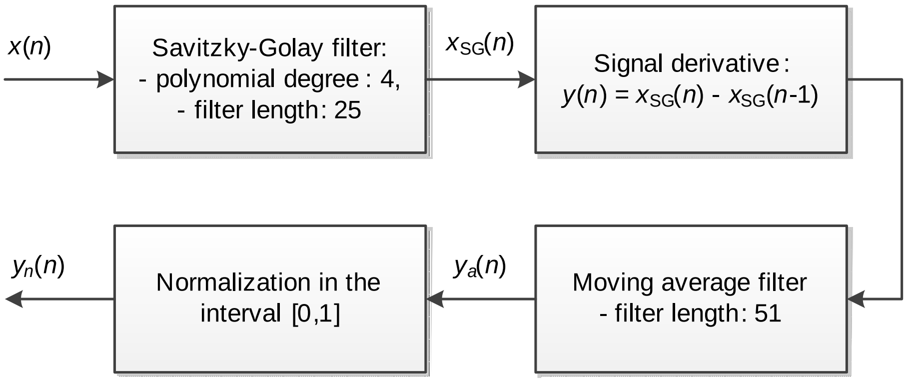

Fig. 1. Filters structure providing the $y_n\,(n)$ signal which local peaks correspond to saccadic eyes movements.

Local maxima of $y_n\,(n)$ can be found using principles of the method presented in [6], which detects the amplitude peaks with zero-crossings of the first derivative of $y_n\,(n)$. The local maximum being the result of saccadic eye movements are discriminated from these related to noise using two parameters. Consequently, a saccade is recognized if the derivative slope and the signal amplitude exceed given thresholds. The condition for the derivative slope that provides the correct saccades location can be defined as $\mathrm{S_{th}} = 0.7w^{-2}$, where w is the acceptable width of the signal peak (in our approach $w = 100$). However, the estimation of the appropriate amplitude level $\mathrm{A_{th}}$ is more difficult. In this work we proposed three different variants of fuzzy clustering based method to find $\mathrm{A_{th}}$.

2.1. ESTIMATION OF THE AMPLITUDE THRESHOLD

Clustering is an unsupervised learning method that divides a set of N objects in c groups (clusters) so that objects (elements) within one group are more similar to each other than to objects outside that group. Elements are usually represented by feature vectors defining the objects properties in the numerical form. Fuzzy clustering is a procedure, which finds the partition on the assumption of partial membership of elements to the formed groups. In the proposed saccades detection method we used Fuzzy c-Means

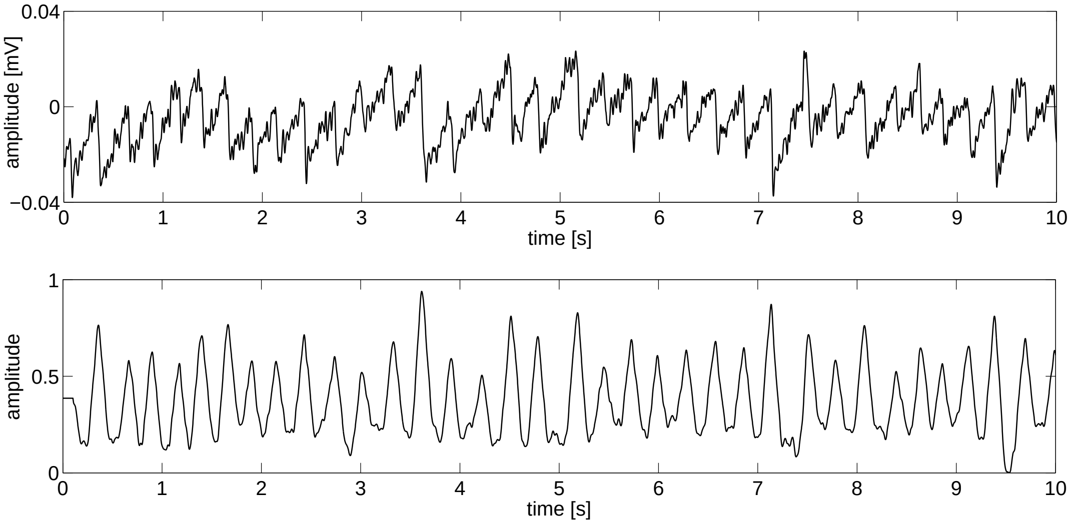

Fig. 2. An example of a real ENG signal corrupted with noise (upper plot) and the corresponding normalized signal (lower plot).

(FCM) [4] algorithm. In the FCM, clusters are represented by prototypes $\mathbf{v}_i$ $(\forall i = 1, 2, \ldots, c)$, defined as the weighted average of the cluster elements:

$$\underset{1\le i\le I}{\forall} \mathbf{v}_i = \frac{\sum_{k=1}^{N} (u_{ik})^2 \mathbf{x}_k}{\sum_{k=1}^{N} (u_{ik})^2} \tag{1}$$

where $\mathbf{x}_k$ is a feature vector representing k-th object and $u_{ik} \in [0, 1]$ is an element of the partition matrix. The partition matrix defines the degree to which objects belong to groups. Consequently, $u_{ik} = 0$ indicates that the k-the element is not a member of i-th group, whereas $u_{ik} = 1$ represents full membership. FCM method provides the partition where the distance of given group objects to the group prototype is smaller than the distances to prototypes of other groups.

As the saccades location is defined with the position of signal peaks of $y_n(n)$, in the first approach (AFCM$_1$) only the samples exceeding the given amplitude threshold τ are clustered [10], [11]. Consequently, the feature vectors are defined as:

$$x_k = y_n(n)|_{y_n(n)>\tau}\,, \tag{2}$$

where τ is assumed as the signal median. The correct amplitude threshold is found by dividing the set of x_k into two groups of samples with "low" ($i = 1$) and "high" ($i = 2$) amplitudes respectively. The value of $\mathrm{A}_{\mathrm{th}}^{(1)}$ is defined as the minimum of elements belonging to the second group, under the condition that their membership degree is higher than a predefined value δ_1:

$$\mathrm{A}_{\mathrm{th}}^{(1)} = \min_k \left(x_k|_{u_{2k}>\delta_1} \right). \tag{3}$$

As the saccades location is defined with the position of local maxima of the $y_n(n)$ signal in the second approach (AFCM$_2$) only the following set of samples is clustered:

$$x_k = y_n(n)|_{y_n(n-1)\le y_n(n)\le y_n(n+1)}\,. \tag{4}$$

After dividing x_k into two groups, we can determine the amplitude threshold analogously to (3):

$$\mathrm{A}_{\mathrm{th}}^{(2)} = \min_k \left(x_k|_{u_{2k}>\delta_2} \right), \tag{5}$$

where δ_2 is the predefined value representing the assumed limit value of membership to the group of samples with "high" amplitude.

A detailed analysis of the $y_n(n)$ signal waveform allows to distinguish yet the third group of the local maxima, that are characterized by "medium" ($i = 3$) amplitude values. Therefore, in the last approach (AFCM_3) three groups ($c = 3$) of the feature vectors (4) are defined. In this case, the high value of membership of the sample to the second cluster denotes high confidence that it represents the saccade. However, the third group consists of elements that are difficult for unambiguous classification. Consequently, the amplitude threshold $\mathrm{A}_{\mathrm{th}}^{(3)}$ is defined as the minimum of samples with high degree of membership to the clusters with "medium" or "high" amplitude (u_{2k} or $u_{3k} > \delta_3$):

$$\mathrm{A}_{\mathrm{th}}^{(3)} = \min_k \left(x_k|_{\max(u_{2k}, u_{3k}) > \delta_3} \right). \tag{6}$$

3. RESULTS AND DISCUSSION

The performance of the proposed variants of the saccades detection method was investigated using artificial as well as real optokinetic nystagmus cycles. The application of artificial signal allows for controlling the exact saccade localization as well as the noise level. Series of OKN cycles were generated with the application of the triangle model of a real optokinetic nystagmus. In our experiments we used the following model specification:
– a directional factor $a_{\mathrm{up}} = 0.075$ [mV/s] and the time duration $t_{\mathrm{up}} = 0.5 + \xi_1$ [s] for the slow phase of OKN where ξ_1 is a random variable of the uniform discrete distribution chosen in the range (0, 0.7) [s],
– a directional factor $a_{\mathrm{dwn}} = 1.05$ [mV/s] and the time duration $t_{\mathrm{dwn}} = 0.04 + \xi_2$ [s] for the saccade (fast phase) where ξ_2 is a random variable of the uniform discrete distribution chosen in the range (0, 0.08) [s].

It allows to obtain variable period of OKN cycles in ENG signal. The accurate saccade position is located in the middle of the saccade slope. Such signal has an infinite SNR. In order to simulate the real conditions of acquisition of ENG signal we added a noise with known value of generalized SNR [9] which was modelled with the symmetric α-stable (SαS) distribution [9]. As the main source of disturbances in ENG signal is the face's muscles activity having an impulsive nature, we used the characteristic exponent (α) of SαS equal to 1.8 [12] and the GNSR level equal to 10 [dB]. Consequently a sequences of 100 random cycles with 83 simulating the real optokinetic nystagmus was generated. A fragment of the artificial ENG signal is presented in Figure 3.

The performance of the proposed procedures was also studied using the real ENG signal registered for the right eye. The application of the one-eye signal only does not limit the validity of our considerations as the same procedure can be applied during analysis of the left eye movements. Optokinetic nystagmus was elicited by a black-and-white stripe pattern stimulation using a rotary cylinder. The ENG signal was recorded using the measurement system based on the Biopac MP-36 unit. The six Ag/AgCl electrodes were placed around the eye providing the measurements of movements in the horizontal direction. The frequency sampling was set to 0.5 kHz. As the reference for the saccades detection we used the expertise of the clinician who was able to recognize 71 OKN cycles in the considered signal.

The efficacy of the automatic amplitude threshold calculation was verified with values of δ_1, δ_2 and δ_3 changed in the range of [0.250, 0.875] with step 0.125. Since the FCM algorithm may lead to a local minimum of the objective function, the calculations were repeated 50 times for various random realizations of initial partition matrix. As the final result we used the mean of the amplitude thresholds calculated for each realization. The saccades detection results can be positive, if a saccade was located in the ENG signal, or negative, when saccade was not found. Consequently, we can evaluate the performance of the fuzzy saccades detection methods using the following indices:

- - sensitivity (S), which is related to the ability to the correct detection of saccades:

$$\mathrm{S} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \tag{7}$$

where TP denotes true positive, FP false positive and FN false negative detections.

- - false discovery rate (FDR), determining the expected rate of false positives:

$$\mathrm{FDR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TP}}, \tag{8}$$

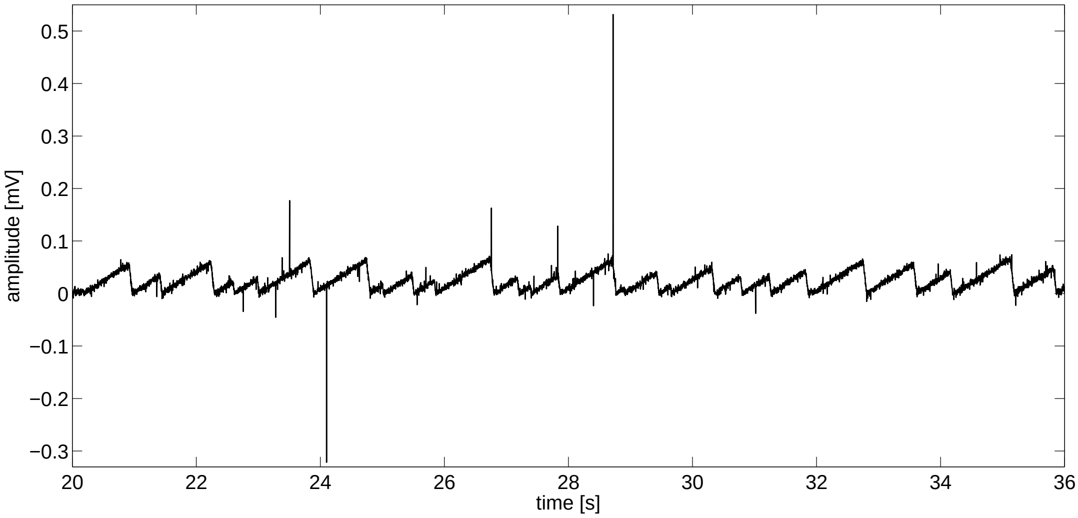

Fig. 3. A fragment of the artificial ENG corrupted with noise (α = 1.8, GSNR = 10 [dB]).

- - the total percentage of correct detections (PCD):

$$\mathrm{PCD} = 1 - \frac{\mathrm{FP} + \mathrm{FN}}{L}, \tag{9}$$

where L is the total number of saccades in the considered signal ($L = 83$ for the artificial and $L = 71$ for the real signal).

The evaluation based on the simultaneous analysis of all the performance indices is difficult, therefore we introduced the quality index QI defined as the geometric mean of S and PCD:

$$\mathrm{QI} = \sqrt{\mathrm{S} \cdot \mathrm{PCD}} \tag{10}$$

Table 1 presents the best results that were obtained when considering the artificial ENG signal.

Table 1. The values of the performance indices obtained with the proposed saccades detection methods using the artificial ENG signal.

	AFCM_1 $\delta_1 = 0.250$	AFCM_2 $\delta_2 = 0.250$	AFCM_3 $\delta_3 = 0.250$
TP	80	80	83
FP	1	1	3
FN	3	3	0
QI	0.958	0.958	0.982
A_{th}	0.414	0.404	0.361

All methods provided the best quality of saccades detection for $\delta_{1,2,3} = 0.250$, however when applying the AFCM_3 we got stable detection results in the wide range of δ_3 parameter (Table 2). The AFCM_3 allowed us also to obtain the 100% of the true positive detection (S = 1.000, FDR = 0.035, PCD = 0.964), but at the cost of three false positives instances. The AFCM_2 is characterized with the lowest computation complexity and provides the high quality of the saccades detection (the same as AFCM_1) for proper values of δ_2.

Table 2 shows the results of the saccades detection quality for the real ENG signal. The best accuracy of the saccades location was obtained for the AFCM_2 and $\delta_2 = 0.75$. Slightly worse results (higher value of the FDR) was noticed for the AFCM_3 and $\delta_3 = 0.875$. The AFCM_1 did not recognize all saccades in the considered signal, however, it was characterized with the zero FDR for all considered values of δ_1. The fragment of the considered signal along with detected saccades was presented in Figure 4.

Table 3 shows the comparison results with the reference saccades detection procedure based on the continuous wavelet transform (CWT) [3] with the constant amplitude threshold. We assumed its value

Table 2. The change of the detection quality index QI for the real ENG signal and different values of δ parameter (the best results are marked).

$\delta_{1,2,3}$	0.250	0.375	0.500	0.625	0.750	0.875
the artificial ENG						
$AFCM_1$	**0.958**	0.928	0.892	0.807	0.783	0.735
$AFCM_2$	**0.958**	0.928	0.843	0.795	0.747	0.663
$AFCM_3$	**0.982**	**0.982**	0.946	0.958	0.928	0.892
the real ENG						
$AFCM_1$	**0.944**	0.915	0.873	0.845	0.761	0.704
$AFCM_2$	0.972	0.972	0.979	0.993	**1.000**	0.944
$AFCM_3$	0.964	0.964	0.964	0.972	0.979	**0.993**

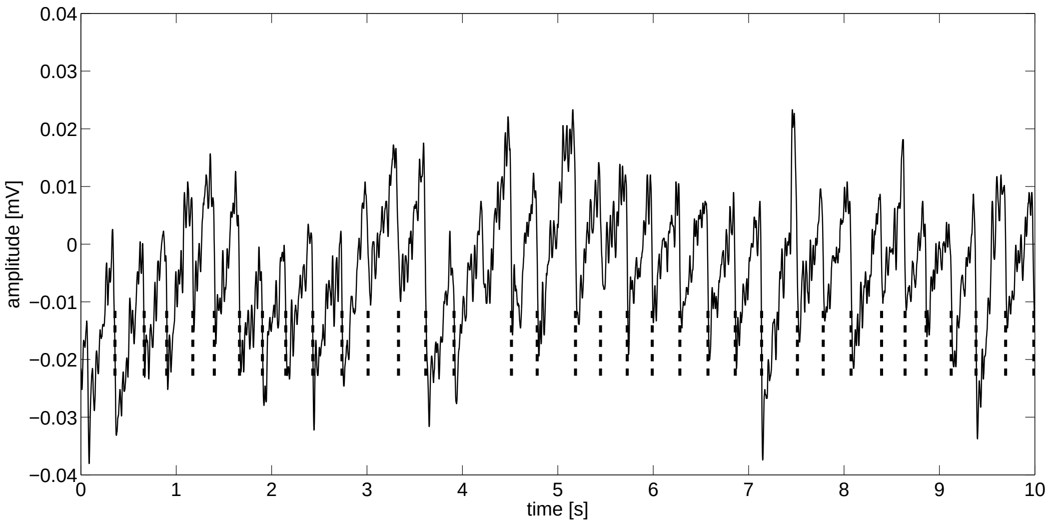

Fig. 4. A fragment of the considered ENG signal along with saccades locations provided by the $AFCM_2$ method ($\delta = 0.75$).

as equal to 50% of the normalized detection function amplitude. All of the proposed methods provided better saccades detection quality.

Table 3. The comparison of the saccades detection quality for the real ENG signal.

	CWT	$AFCM_1$ $\delta_1 = 0.250$	$AFCM_2$ $\delta_2 = 0.750$	$AFCM_3$ $\delta_3 = 0.875$
S	0.901	0.944	1.000	1.000
FDR	0.045	0.000	0.000	0.014
PCD	0.859	0.944	1.000	0.958
Q	0.880	0.944	1.000	0.979
A_{th}	0.500	0.526	0.505	0.462

Clustering the samples being the possible local maxima of the ENG signal leads to better estimation of the proper amplitude threshold level and allows for the correct saccades detection. Both variants of the FCM based method the $AFCM_2$ and the $AFCM_3$ provided high sensitivity of the detection. With the $AFCM_2$ we obtained better results for the real ENG signal, however the $AFCM_3$ was less sensitive to the proper selection of δ. Unfortunately, we can not provide the automatic method for calculation of the δ ensuring the best quality of the saccades location. However, our experiments showed that values from the range $[0.6 - 0.8]$ work reasonably well for both algorithms when considering the real ENG signal.

4. CONCLUSIONS

The paper presents different variants of the method for automatic detection of saccadic eyes movements. The proposed algorithms are based on the proper filtering of the electronystagmography signal providing a waveform whose peaks are related to the dynamic changes of the signal being the result of the fast eyes rotation. The correct recognition of the local maxima corresponding to saccades was obtained by the means of fuzzy c-means algorithm. Different definition of the clustered sets of samples and various specification of the clustering algorithm provided different quality of the detection. The application of fuzzy clustering to the selected set of samples allows for efficient positioning of saccades, which is required for the precise definition of nystagmus cycle parameters and the same, accurate modelling of the eyes movements.

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