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Vision-Based Absence Seizure Detection

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Abstract—**In order to diagnose epilepsy, neurologists rely on their experience, performing an equal assessment of the electroencephalogram and the clinical image. Since misdiagnosis reaches a rate of 30% and more than one-third of all epilepsies are poorly understood, a need for leveraging diagnostic precision is obvious. With the aim at enhancing the clinical image assessment procedure, this paper evaluates the suitability of certain facial expression features for detecting and quantifying absence seizures. These features are extracted by means of time-varying signal analysis from signals that are gained by applying computer vision techniques, such as face detection, dense optical flow computation and averaging background subtraction. For the evaluation, video sequences of four patients with absence seizures are used. The classification performance of a C4.5 decision tree shows accuracies of up to 99.96% with a worst percentage of incorrectly classified instances of 0.14%.**

I. Introduction

Epilepsy is one of the most common disorders of the brain. The estimated number of children and adolescents in Europe with active epilepsy is 0.9 million (prevalence 4.5-5.0 per 1000) [1]. Diagnosis of this disorder is a challenging task, which is based on the experience of the neurologist and is prone to subjective or biased judgment of the latter or a caring person. Misdiagnosis of epilepsy reaches a rate of 30% [2] and has tremendous consequences on quality of life of the wrongly diagnosed patient, experiencing side effects of medication, unnecessary driving restrictions and serious employment problems [3]. A widely accepted classification of epileptic seizures and epileptic syndromes has been established by the International League Against Epilepsy (ILAE) and provides a common language that facilitates epilepsy diagnosis [4], [5]. These proposals are subject to continuous revisions [6]–[8], which underlines the fact that epilepsy diagnosis is characterized by practical, e.g. not being able to give a recognized syndromic diagnosis to every patient, and dynamic aspects, as seizure types and syndromes change due to advances in neuroscience (e.g. genomics, molecular biology) that provide new information [6]. The latest report of the ILAE presents a revised terminology and concepts for organization of seizures and epilepsies on the basis of the level of specificity – i.e. the diagnostic precision – indicating the importance of the latter [8]. Moreover, it states that "(…) one-third or more of all epilepsies are the most poorly understood, and represent perhaps the most fertile area for future research (…)" [8].

The trends mentioned above reveal the need for leverage in diagnostic precision. Although great advances in the area of electroencephalogram (EEG) analysis have been made (e.g. [9]), the same cannot be stated for the field of analyzing and quantifying ictal phenomenology (i.e. the clinical image). Therefore, this paper approaches the aforementioned need from the perspective of analyzing the clinical image. This is done through the application of computational methods based on computer vision, signal processing and machine learning.

These methods are applied for the analysis of the facial expression of patients with absence seizures. The objective is to identify one or more metrics that describe the clinical image in a quantitative manner, thus facilitating the disease diagnosis and treatment. Absence seizures have been chosen as an initial object of research, as they exhibit a stereotypical expression and occur frequently enough for the collection of an adequate dataset. Moreover, focusing on just one seizure type is a necessity at this point in order to reduce the problem dimensionality, as more than 20 different seizure types exist [8] and more than 40 possible facial expression descriptions can be linked to epilepsy [10], [11].

A. *Absence seizures*

Absence seizures are generalized seizures with three subtypes, according to ILAE [8]: typical absences, atypical absences and absences with special features (myoclonic absence and eyelid myoclonia). Typical absences are brief, generalized epileptic seizures of sudden onset and termination. They present a cluster of clinico-EEG manifestations that may be syndrome-related, as for example in Childhood Absence Epilepsy, in which typical absences persist as the only seizure type. Typical absences most frequently occur between 4 and 9 years of age. Transient impairment of consciousness (severe, moderate, mild or inconspicuous) is an essential component of typical absences and may be the only clinical symptom (simple absences). When the transient impairment of consciousness is combined with other manifestations (clonic, myoclonic, atonic,

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autonomic components and automatisms) absences are characterized as complex [12].

Clonic and myoclonic symptoms are particularly frequent at the seizure onset. The most common are clonic or myoclonic jerking of the eyelids, eyebrows, and eyeballs, including random or repetitive eye closures and horizontal or vertical nystagmus-like ocular movements. Perioral myoclonias at the corner of the mouth and jerking of the jaw are less common, while clonic or myoclonic jerks of the head are even less frequent. Tonic components may affect extensor or flexor muscles symmetrically or asymmetrically. The eyes and the head may be drawn backwards (retropulsion) or to one side. Atonic symptoms are not unusual and may lead to drooping of the head. Autonomic components consist of pallor and less frequently sweating, flushing, salivation etc. Automatisms usually occur when cognition is impaired and may be delayed, 4-6 sec after onset. The most common automatisms are lip licking, smacking, swallowing, chewing, shoulder shrug and mute speech movements. [13]

The above descriptions reveal the complexity of the problem at hand, but they also indicate that head motion, eye- and mouth-related motion is heavily involved in absence seizures. Therefore, in the context of facial expression analysis, this work focuses on the regions of the eyes and the mouth.

B. Related work

Advances in facial expression analysis are mainly driven by research efforts in human emotion recognition. A thorough review is presented in [14]. Most automatic facial expression analysis systems attempt to recognize a small set of prototypic emotional expressions (e.g. disgust, fear, joy etc.), although emotion is more often communicated by subtle changes in one or a few discrete facial features, such as tightening of the lips in anger or obliquely lowering the lip corners in sadness. Therefore the Facial Action Coding System [15], a human-observer-based coding system designed to detect subtle changes in facial features as a result of facial muscle activity, is often adopted.

Regarding epilepsy, a thorough review in vision-based human motion analysis is presented by Pediaditis et al. [16]. Applicable methods can be separated into marker-free and marker-based methods, both of which have been successfully applied in the analysis and classification of specific seizure types and the related motion patterns. Considering facial expression analysis in epilepsy, only one reference can be found that uses a model-based approach to calculate the variation of model parameters by fitting a 3D active appearance model [17].

II. METHODS

A. Feature extraction

The basic feature extraction procedure has already been applied by the authors on epileptic-like videos for feature selection and is closely described in [18]. A short description of this procedure follows in favor of comprehensibility. Any modifications and updates to the basic procedure are additionally described wherever applicable.

At first, the regions of interest (ROI), namely the area of the eyes and the mouth, as shown in Fig. 1 are automatically detected using the Viola-Jones detection algorithm. For each region, six time-varying signals are extracted using two methods. The first, dense optical flow [19], provides a velocity vector field for each frame, which forms the basis for estimating the five time-varying signals depicting the maximum magnitude, the mean magnitude, the mean vector angle, the mean magnitude weighted by the mean vector angle and the normalized pixel area of thresholded magnitudes. The second method, the averaging background [20], is being used for gaining the last time-varying signal, namely the normalized pixel area of all pixel values outside a threshold, defined by subtracting consecutive frames and averaging over the background. For each of these signals, six features are calculated by employing a running window (new to this procedure) with a length of 2 sec., which is defined by the minimum duration of a seizure (cf. TABLE I.). The six calculated features are the following:

- “VTI”, the variance of time intervals between adjacent extrema, as a measure for rhythmicity.
- “ENR”, the energy ratio of the last 75% to the first 25% of the autocorrelation sequence, as a measure for the motion manifested as quasi-periodic spikes (randomness).
- “25SPF”, the 25% spectral power frequency defined as the upper bound of the frequency band starting at 0 Hz that contains 25% of the total spectral power. Seizures containing isolated sharp spikes generate a broader band while seizures with many (near periodic) spikes produce a narrower.
- “PW1”, the total spectral power in the interval of [0, 3] Hz.
- “PW2”, the total spectral power in the interval of]3, 6] Hz.
- “DFR”, the dominant frequency in the power spectrum.

Additional modifications and updates to the basic procedure described in [18] include the following: All features are now calculated in a C++ environment, using OpenCV 2.3.1 [21] and the GNU Scientific Library 1.15 [22].

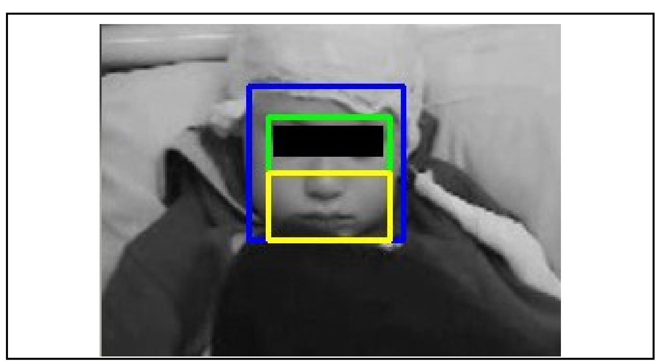

Figure 1. Automatic detection of the regions of interest.

The power spectral density is estimated with the discrete Fourier transform, while a strict filtering rule rejects all windowed samples including less than 75% of detected ROIs. For the rest of the windowed samples missing values are interpolated by a cubic spline interpolation.

B. Evaluation

The suitability of the aforementioned features to quantitatively assess the clinical image was evaluated using a machine learning/ classification method, the well-known C4.5 decision tree [23], as provided by the data mining software Weka 3.6 [24] (weka.classifiers.trees.J48 -C 0.25 -M 2). At each node of the tree, C4.5 chooses one attribute of the data that most effectively splits its set of samples into subsets enriched in one class or the other.

The evaluation used video content recorded at the Pediatric Unit of the University Hospital of Heraklion, Crete during first-time diagnostic long-term video-EEG recordings of four patients. Informed consent was acquired for using the videos in research. Each recording was annotated based on the video and the EEG by a professional pediatric neurologist, resulting in the dataset shown in TABLE I. It consists of a total of 77 seizures, constituting the "absence seizure" class.

The video sequences for the control class are randomly selected sections showing no seizure activity, taken from the four patient's video-EEG recordings. Finally, a separate stratified 10-fold cross-validation was performed for each feature-set, computed from a time-varying signal for either the eyes or the mouth. Pairs of feature-sets, for the eyes and the mouth, taken simultaneously from the respective time-varying signal were evaluated as well.

III. RESULTS

The feature extraction procedure described in Section II.A returned a total of 848 instances for the "absence seizure" class and 19830 instances for the control class. The results of the stratified 10-fold cross-validation are presented in TABLE II. All time-varying signal extraction methods performed exceptionally well with an average accuracy of 99.91 %.

TABLE I. PATIENT DATASET

Patient	***1***	***2***	***3***	***4***
Age	5	10	10	6
Gender	male	female	male	male
No. of annotated seizures	4	9	19	45
Average seizure duration (sec.)	8	6	2	2
Diagnosis	Typical absences	Typical absences	Absences with myoclonic jerks	Absences with myoclonic jerks

The best results are highlighted in grey showing an accuracy of up to 99.96 %. Analysis of the tree structure[1] reveals which features have the highest discriminative power in each case. It has resulted that e.g. only the DFR and 25SPF have been used for decision making, when calculated from the max. magnitude time-varying signal at the mouth. This signifies that the existence of periodic movements – since in this case lower values for 25SPF decide in favor of an absence seizure – and a different dominant frequency separate the "absence seizure" class from the control class. These two features, namely DFR and 25SPF, generally dominate in the decision making process for the mouth area with VTI appearing sparsely in deeper nodes.

TABLE II. CLASSIFICATION RESULTS

Time-varying signal/ method	**Classification metrics**				***Class***[a]
	Tree size	***Accuracy %***	***TP Rate***	***FP Rate***	
Max. magnitude (eyes)	67	99.898	0.98	0	AS
			1	0.02	NS
Max. magnitude (mouth)	27	99.918	0.987	0	AS
			1	0.013	NS
Mean magnitude (eyes)	73	99.903	0.98	0	AS
			1	0.02	NS
Mean magnitude (mouth)	33	99.957	0.989	0	AS
			1	0.01	NS
Mean angle (eyes)	47	99.947	0.989	0	AS
			1	0.011	NS
Mean angle (mouth)	59	99.865	0.974	0	AS
			1	0.026	NS
Mean magnitude weighted by angle (eyes)	67	99.884	0.975	0	AS
			1	0.025	NS
Mean magnitude weighted by angle (mouth)	73	99.865	0.968	0	AS
			1	0.032	NS
Thresholded area (eyes)	57	99.884	0.974	0	AS
			1	0.026	NS
Thresholded area (mouth)	45	99.903	0.98	0	AS
			1	0.02	NS
Area, averaging backround (eyes)	29	99.952	0.988	0	AS
			1	0.012	NS
Area, averaging backround (mouth)	37	99.961	0.991	0	AS
			1	0.009	NS

a. AS = absence seizure; NS = no seizure

[1] Detailed results and tree structures can be provided upon request from the corresponding author.

For the eyes, the optical flow-based methods produce quite large decision trees, which make the feature assessment difficult, although DFR is the most often utilized feature for decision making, with PW1, PW2 and 25SPF appearing infrequently at deeper nodes (>20). An exception forms 25SPF computed from the thresholded area, which is the main feature dominating in the respective tree model. Special attention should be given to the features derived from the averaging background signals, which form the smallest trees with the highest accuracies. For the eyes, 25SPF is the sole dominant feature. For the mouth the decision nodes follow a rather strict order starting at the top of the tree with DFR, then using PW2, followed by VTI and finally 25SPF. These relate to the – expected – more complex motion patterns performed by the lip muscles. The classification results using the pairs of feature-sets, describing together the eyes and the mouth, were slightly inferior with an average accuracy of 99.87 %. The fact that no benefit could be achieved from the usage of both feature-sets indicates that motion patterns in the eyes and mouth probably appear in an unsynchronized manner, since the features were taken at the same time-point. The tree structure analysis with respect to feature properties revealed similar results to those presented in the previous paragraphs. Finally, ENR does not appear in any tree node, indicating its weak discriminative power.

IV. Conclusion

The classification and tree analysis outcome provides promising results for the determination of quantitative metrics describing absence seizures, such as the 25SPF and DFR, calculated e.g. from the averaging background area signal. The high accuracy of the classification suggests that application of the presented methods in an unobtrusive seizure detection environment and the development of a robust decision support system are possible. Nevertheless, given the fact that only four patients could be analyzed so far makes the establishment of those metrics yet uncertain. The performance of the proposed analytical pipeline and methods on a greater patient pool has to be tested, while this can be considered as the stimulation to further analysis even with other seizure types. Future work will also consider engaging the Facial Action Coding System mentioned in Section I.B, since its application might provide more detailed information on the facial expression patterns of patients with epilepsy. Obviously, the occlusion problem still presents a big challenge. In fact, many of the seizure-annotated sequences did not reach the feature extraction phase because the face was too far out of plane or partially occluded, such that it did not get detected at all. Usage of more cameras or other advanced methods (e.g. [25]) could improve the face/ eye-detection process.

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