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TEMoD: Target-Enabled Model-Based De-Drifting of the EOG Signal Baseline using a Battery Model of the Eye

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Abstract— **The electrooculography (EOG) signal baseline is subject to drifting, and several different techniques to mitigate this drift have been proposed in the literature. Some of these techniques, however, disrupt the overall ocular pose-induced DC characteristics of the EOG signal and may also require the data to be zero-centred, which means that the average point of gaze (POG) has to lie at the primary gaze position. In this work, we propose an alternative baseline drift mitigation technique which may be used to de-drift EOG data collected through protocols where the subject gazes at known targets. Specifically, it uses the target gaze angles (GAs) in a battery model of the eye to estimate the ocular pose-induced component, which is then used for baseline drift estimation. This method retains the overall signal morphology and may be applied to non-zero-centred data. The performance of the proposed baseline drift mitigation technique is compared to that of five other techniques which are commonly used in the literature, with results showing the general superior performance of the proposed technique.**

I. INTRODUCTION

Electrooculography (EOG) is an eye movement recording technique which records the electrical signal generated by the human eyes. Specifically, there exists a potential difference between the cornea and the retina, known as the corneo-retinal potential, which allows the eye to be modelled by an electrical dipole having its positive pole at the cornea and its negative pole at the retina [1]. This creates an electrical field and the electrical signal from this field is recorded using electrodes which are attached to the face in close proximity to the eyes. The typical electrode setup comprises a pair of electrodes which is horizontally-aligned with the ocular sockets and attached next to the outer canthi, and another two electrodes which are aligned vertically with one eye and attached above and below the eye [2].

The EOG signal baseline is subject to drifting and this is due to background signal interference, electrode polarisation and variations in electrode contact pressure and skin resistance [3]–[5]. This poses one of the main challenges to EOG signal processing because, unless it is addressed, it may be misinterpreted as slow ocular rotation. In the literature, the baseline drift has been addressed using several different techniques. Specifically, the simplest technique involves no specific pre-processing but rather requires the user to gaze at a pre-determined location on the screen either deliberately or periodically and the system is reset accordingly. Another technique involves computing the derivative/difference of the recorded EOG signals. This, however, distorts the overall morphology of the EOG signals, losing their absolute ocular pose-dependent DC characteristics. This signal distortion is generally also the case when the baseline drift is mitigated by high-pass filtering the data because, depending on the choice of the cut-off frequency, the filtered EOG signals would be characterised by a gradual decay towards zero. Conversely, there are other techniques which estimate the baseline component, either by fitting a polynomial function or through multilevel 1D wavelet decomposition. This baseline estimate is then subtracted from the recorded EOG data to yield the baseline drift mitigated EOG signals. These two baseline estimation-based techniques and high-pass filtering, however, are only applicable to zero-centred data which implies that the average point of gaze (POG) has to lie at the primary gaze position. The reader is directed to the work of Barbara *et al.* [5] for a comprehensive quantitative and qualitative review of these different techniques.

In this work, we propose a novel EOG signal baseline de-drifting technique which does not require the data to be zero-centred nor disrupts the overall absolute ocular pose-dependent DC characteristics. These characteristics may be useful in applications such as for the automated evaluation of the Arden Ratio [6] used for the diagnosis of ophthalmic disorders, or for analysing the eye-head coordination during gaze shifts such as in [7]. In the proposed technique, the subject gazes at prescribed targets and these target gaze angles (GAs) are used within a battery model of the eye to estimate the ocular pose-induced component, which is then used to estimate the baseline component. The battery model used in the proposed **t**arget-**e**nabled **mo**del-based **d**e-drifting (TEMoD) method relates the monopolar EOG potential to the distances between the electrode and the cornea and retina centre points of the two ocular globes [8], [9]. This work also compares the de-drifting performance of the proposed TEMoD method to the performance of the reviewed baseline drift mitigation techniques commonly used in this domain.

Hence, the rest of the paper is divided as follows. Section II discusses the nomenclature, the data acquisition protocol and the proposed baseline drift mitigation method. This is followed by Section III where the de-drifting perfor-

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mance results obtained using the proposed method and other techniques used in the literature are presented and discussed. Section IV concludes this paper.

II. METHOD

This section presents the nomenclature and the data acquisition protocol followed in this work. The proposed TEMoD method is also presented and discussed.

A. Nomenclature

In this work, the subject is assumed to be placed at a distance D away from a screen having the midpoint between the two ocular globes $\mathbf{O}$ aligned with the normal projected from the centre of the screen $\mathbf{O}_s$, as shown in Fig. 1. When the subject focuses their POG on a fixed target $\mathbf{T}$ on the screen, the horizontal and vertical angles subtended by the line $\mathbf{OT}$ and the normal $\mathbf{OO}_s$ denote the horizontal and vertical GAs, θ_h and θ_v, respectively, which may be denoted collectively as $\boldsymbol{\theta} = (\theta_h, \theta_v)$. The orientation of the ocular globes may be expressed separately in terms of the corresponding ocular angles (OAs), specifically in terms of the azimuths $\phi_h^{(l)}$ and $\phi_h^{(r)}$ and elevations $\phi_v^{(l)}$ and $\phi_v^{(r)}$ of the left and right eyes, respectively, which are defined as shown in Fig. 1.

B. EOG Data Acquisition

The signal acquisition protocol used in this work was approved by the University Research Ethics Committee of the University of Malta and all participants provided their informed prior consent. EOG data was recorded from six subjects (2 males and 4 females, with mean age of 24.7±3.1 years), having normal or corrected-to-normal vision. Subjects were seated approximately 60 cm away from a 24-inch monitor, with their heads rested on a chin-and-forehead rest to avoid head movement during acquisition.

The subjects were asked to focus their POG on a target cue which appeared at different locations on the monitor. Specifically, a number of trials, each 4 s long, were recorded consecutively for each subject. At the beginning of a given trial j, the cue was initially displayed at position P_{1_j} and, after 1 s the cue was moved to a different position P_{2_j} for another 1 s. During the last 2 s of each trial, the cue changed colour to instruct the subject to perform a blink. Therefore, in a given trial j, the user is instructed to perform (i) a saccade from $P_{2_{j-1}}$ to P_{1_j} during the first 1 s interval, (ii) a saccade from P_{1_j} to P_{2_j} during the next 1 s interval, and (iii) a blink in the last 2 s interval. The initial target position P_{2_0} was set to the centre of the screen. In this work, zero-centred and non-zero-centred EOG data were recorded in two separate datasets, which are henceforth denoted as D_{ZC} and D_{NZC}, respectively. Specifically, D_{ZC} was comprised of 300 trials, wherein the position P_{1_j} in each trial was random whereas P_{2_j} was always set to the centre of the screen, for all $j = 1, ..., 300$. In contrast, D_{NZC} was comprised of 200 trials, where the positions P_{1_j} and P_{2_j} for all $j = 1, ..., 200$ were random. Since two different gaze targets were shown in each trial, D_{ZC} and D_{NZC} contained $N_{ZC} = 600$ and $N_{NZC} = 400$ saccade windows, respectively.

The eye movements carried out were recorded using a g.USBamp bio-signal amplifier (g.tec medical engineering GmbH, Austria). A conventional electrode configuration was used, where two electrodes were aligned horizontally with the eyes and attached next to the outer canthi, whereas two other electrodes were aligned vertically with the subject's right eye and mounted above and below the corresponding ocular socket. A reference and a ground electrode were attached on the subject's left mastoid and forehead, respectively. The EOG data was recorded at a 256 Hz sampling frequency and was filtered using a 30 Hz low-pass filter. In this work, the bipolar EOG signals computed from the two horizontally-aligned and the two vertically-aligned electrodes were used to yield what are commonly referred to as the horizontal and vertical EOG channels, denoted by EOG_{1_t} and EOG_{2_t}, respectively.

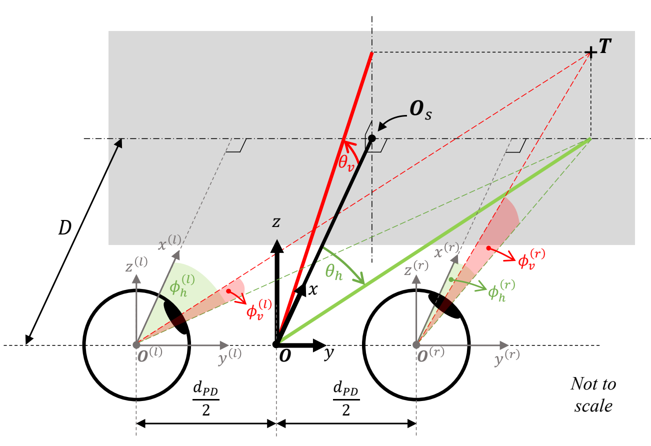

Fig. 1. Nomenclature used in this work, where d_{PD} denotes the inter-pupillary distance.

C. The Battery Model

The battery model used in this work was originally proposed by Shinomiya *et al.* [8]. This only modelled the monopolar EOG potential due to a single ocular globe, but it has been recently augmented by Barbara *et al.* [9] to cater for the influence of both ocular globes [8], [9]:

$$V_i = \frac{I}{4\pi\sigma}\left(\frac{1}{d_{c_i}^{(L)}} - \frac{1}{d_{r_i}^{(L)}}\right) + \frac{I}{4\pi\sigma}\left(\frac{1}{d_{c_i}^{(R)}} - \frac{1}{d_{r_i}^{(R)}}\right) \quad (1)$$

where V_i is the monopolar EOG signal recorded by an arbitrary electrode i, and $d_{x_i}^{(y)}$ denotes the distance between the electrode and the left/right cornea/retina, where $x \in \{c, r\}$ denoting the cornea or retina, respectively, and $y \in \{L, R\}$ denoting the left or right ocular globe, respectively. The distances $d_{x_i}^{(y)}$ are computed as in Barbara *et al.* [9]. Additionally, I is the current flowing within the ocular globe from the retina to the cornea, and σ denotes the ocular globe surface electrical conductivity [8], [9].

D. The Proposed TEMoD Method

An arbitrary EOG signal EOG_{i_t} may be assumed to be comprised of three components; namely (i) an ocular pose-induced component $f_i(\boldsymbol{\theta}_t)$, (ii) a baseline drift component b_{i_t} and (iii) noise w_{i_t}. Hence, EOG_{i_t} may be represented as:

$$EOG_{i_t} = f_i(\boldsymbol{\theta}_t) + b_{i_t} + w_{i_t} \tag{2}$$

As discussed previously, the proposed method requires the GAs $\{\boldsymbol{\theta}_s\}$ corresponding to the target cues to which the user was asked to attend to during EOG signal acquisition for all $s = 1, ..., N_s$ to be known, where N_s denotes the total number of saccade windows, that is $N_s = N_{ZC}$ or $N_s = N_{NZC}$, as appropriate. As shown in the method flow-diagram in Fig. 2, these are used to estimate the ocular pose-induced component $\hat{f}_i(\boldsymbol{\theta}_t)$ for all channels $i = 1, ..., N$, where N denotes the total number of EOG channels to be de-drifted. Specifically, considering channel i and saccade s, $\hat{f}_i(\boldsymbol{\theta}_s)$ is initially obtained by using the target GAs $\boldsymbol{\theta}_s$ in the battery model of (1). The instant at which the transition from $\hat{f}_i(\boldsymbol{\theta}_{s-1})$ to $\hat{f}_i(\boldsymbol{\theta}_s)$ occurs is aligned with the instant at which the s^{th} saccade occurs, thus compensating for the human reaction time to attend to the target. Specifically, the transition is set to occur at the mean $t_i^{(s)}$ across all channels $i = 1, ..., N$, where $t_i^{(s)}$ denotes the instant in the s^{th} saccade window at which maximum velocity occurs.

After repeating this for all $s = 1, ..., N_s$, $\hat{f}_i(\boldsymbol{\theta}_t)$ is then subtracted from the corresponding recorded EOG signals EOG_{i_t}, to yield $r_{i_t} \approx b_{i_t} + w_{i_t}$, comprising the residual noise and baseline components, as in (2). The low-frequency baseline component $\hat{b}_{i_t}$ may then be estimated from r_{i_t} using multilevel 1D wavelet decomposition using db6 wavelets, specifically using a reconstruction level of 11, which lies in the optimal range determined in the review of Barbara *et al.* [5]. Note that, in order not to allow the blink-induced EOG displacements distort the estimated baseline component, blinks are initially detected and removed using a standard template matching-based technique as in Bulling *et al.* [10] on the differenced vertical EOG channel. The baseline drift-mitigated EOG signals, denoted by EOG'_{i_t}, are then obtained by subtracting $\hat{b}_{i_t}$ from the corresponding monopolar EOG channel EOG_{i_t}. Note that the battery model and the multilevel wavelet decomposition method used for the estimation of the ocular pose-induced and baseline components of the EOG signal, respectively, may be replaced by suitable alternatives. Fig. 3 shows the EOG signals obtained after they are de-drifted using the proposed technique.

E. De-Drifting Performance Evaluation

This work compares the de-drifting performance of the proposed technique to the baseline drift mitigation techniques reviewed in Section I which are commonly used in the literature. Therefore, the techniques implemented in this work include: (i) frequent resetting, (ii) signal differencing, (iii) high-pass filtering, (iv) polynomial fitting, (v) multilevel 1D wavelet decomposition, and (vi) the proposed TEMoD method. The parameters used in techniques (i)-(v) were set to the optimal values as determined in the review of Barbara *et al.* [5]. The baseline de-drifting performance was also assessed in a similar way to Barbara *et al.* [5], specifically by calculating the GA estimation error obtained using the de-drifted EOG signals for each of these six techniques. To this end, a two-channel input linear regression model, using features extracted from the horizontal and vertical EOG channels simultaneously, was used to estimate the GAs. Such a modelling technique was found to yield a generally superior estimation performance when compared to using a pair of linear regression models, one for each EOG channel [11].

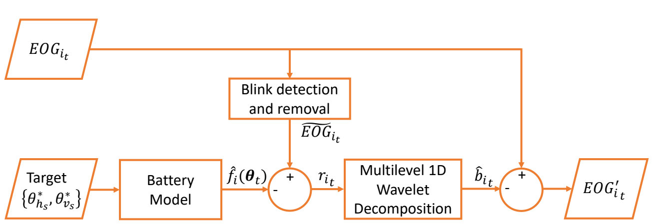

Fig. 2. EOG signal baseline de-drifting flow diagram.

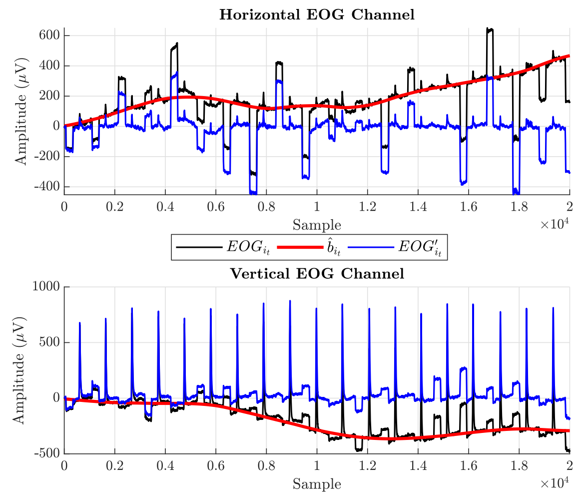

Fig. 3. Baseline drift mitigation using the proposed method.

A cross-validation procedure was used where specifically, the EOG signals recorded for each subject in datasets D_{ZC} and D_{NZC}, as appropriate, were divided into three equally-sized subsets, denoted as S_A, S_B and S_C, respectively. S_A was used to determine the electrode positions required for the battery model in the proposed method, which were estimated as in Barbara *et al.* [9]. S_B was used to determine the EOG-to-GA regression model weights, whereas S_C was used to quantify the GA estimation performance. This procedure was repeated for all six combinations of the three subsets. In order not to bias the results, those windows in which the subject was not compliant with the instructions, such as blinking while the subject was expected to perform a saccade or performing return saccades prematurely, were excluded resulting in 100 and 66 saccade windows in each subset using D_{ZC} and D_{NZC}, respectively.

In order to quantify the GA estimation performance, the horizontal and vertical GA estimates $\hat{\theta}_{h_t}$ and $\hat{\theta}_{v_t}$ were initially obtained from the de-drifted horizontal and vertical EOG channels, EOG'_{1_t} and EOG'_{2_t}, respectively. The mean GA estimates $\bar{\hat{\theta}}_{h_s}$ and $\bar{\hat{\theta}}_{v_s}$ obtained in the interval between

TABLE I

DE-DRIFTING PERFORMANCE RESULTS OF THE PROPOSED TECHNIQUE AND OTHER TECHNIQUES COMMONLY USED IN THE LITERATURE.

	Zero-Centred Data												**Non-Zero-Centred Data**	
	Proposed TEMoD Method		**Frequent Resetting**		**Signal Differencing**		**High-pass Filtering**		**Polynomial Fitting**		**Multilevel 1D Wavelet Decomposition**		**Proposed TEMoD Method**	
Subject	$E_h(^\circ)$	$E_v(^\circ)$	$E_h(^\circ)$	$E_v(^\circ)$	$E_h(^\circ)$	$E_v(^\circ)$	$E_h(^\circ)$	$E_v(^\circ)$	$E_h(^\circ)$	$E_v(^\circ)$	$E_h(^\circ)$	$E_v(^\circ)$	$E_h(^\circ)$	$E_v(^\circ)$
S1	0.66	0.95	0.85	1.26	0.74	1.00	1.74	1.50	1.73	1.61	2.30	1.60	0.80	0.99
S2	0.81	1.81	0.86	1.84	0.87	1.46	1.78	2.67	1.87	3.12	1.96	2.19	0.90	1.60
S3	1.13	1.55	1.18	1.59	0.87	1.31	2.14	1.86	2.46	2.27	2.29	1.98	0.80	1.76
S4	1.67	2.15	1.83	2.20	1.18	1.45	2.68	2.77	2.83	3.02	2.99	2.70	1.70	1.86
S5	1.40	1.87	1.95	2.45	1.05	1.30	2.50	2.68	2.96	3.12	2.46	2.12	1.35	1.45
S6	0.94	1.62	0.98	1.61	1.04	1.88	1.73	1.87	1.84	1.91	2.12	2.04	1.11	1.51
Average	**1.10± 0.38**	**1.66± 0.40**	**1.27± 0.49**	**1.82± 0.44**	**0.96± 0.16**	**1.40± 0.29**	**2.10± 0.41**	**2.23± 0.55**	**2.28± 0.54**	**2.51± 0.67**	**2.35± 0.36**	**2.11± 0.36**	**1.11± 0.36**	**1.53± 0.30**

the occurrence of the s^{th} saccade and the end of the corresponding 1 s time window in which it was performed were then evaluated. The error $(e_{h_s}, e_{v_s}) = \left(\theta^*_{h_s}, \theta^*_{v_s}\right) - \left(\bar{\hat{\theta}}_{h_s}, \bar{\hat{\theta}}_{v_s}\right)$ was evaluated, where $\theta^*_{h_s}$ and $\theta^*_{v_s}$ denote the target horizontal and vertical GAs for the s^{th} saccade, respectively, and used to work out the mean horizontal and vertical GA estimation errors, E_h and E_v, respectively. It is noteworthy that since for the signal differencing method the EOG potential displacements are used to estimate the gaze displacements, the errors presented in this case are gaze displacement estimation errors.

III. RESULTS AND DISCUSSION

The cross-validated performance results obtained when the six baseline drift mitigation techniques were applied to zero-centred data D_{ZC} are tabulated in Table I. These results show that the proposed TEMoD method is superior when compared to the rest of the techniques, except for the signal differencing method. It is however noteworthy that, although both the signal differencing and the proposed methods may be applied to non-zero-centred data, the better performance obtained using signal differencing comes at the cost of disrupting the overall morphology of the EOG signals, as gaze movement-induced displacements are transformed into spikes. This may be undesirable, for example when analysing slow eye movements, such as smooth pursuits and vestibulo-ocular reflexes (VORs). Furthermore, for absolute POG estimation, valid saccade spikes would need to be detected, transformed into equivalent gaze displacements and accumulated. This whole process may result in missed small gaze-movements as well as accumulation of error [5].

Since the proposed method is generally applicable to non-zero-centred data, this technique was also applied to D_{NZC}. The results obtained are shown in Table I, showing comparable error as for the zero-centred data, demonstrating that the proposed technique may be applied to EOG data which does not necessarily possess zero-centred characteristics.

IV. CONCLUSION

This work has proposed a novel EOG signal baseline drift mitigation technique which uses the target GAs, which the user attended to during EOG signal acquisition, within a battery model of the eye to obtain an estimate of the ocular pose-induced component. The proposed TEMoD technique was shown to compare well with other baseline drift mitigation techniques used in the literature, but comes with the added advantages of retaining the overall morphology and DC characteristics of the EOG signal and being applicable to EOG data which may not necessarily be zero-centred. This makes the method suitable for applications requiring a controlled test during which the subject is requested to gaze at specific points of regard, for example for the evaluation of the Arden Ratio [6] used for the diagnosis of ophthalmic disorders, or for analysing the eye-head coordination during gaze shifts such as in [7]. Future work will also consider algorithmic mechanisms to mitigate subject compliance in attending to the targets.

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