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Leveraging FMCW Radar for Eye Blink Detection: A Comprehensive Exploration and Evaluation

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***Abstract*—The detection of eyeblinks serves as one of crucial human indices for evaluating physiological and psychological states in diverse applications. This research is focused on the use of Frequency Modulated Continuous-Wave (FMCW) radar technology for monitoring eye blinks, with a comprehensive investigation of eyeblink detection methods and the impact of blink interval, change of gaze, head movements, wearing glasses, and presence of nearby people. In contrast to previous studies, which often overlooked these factors, our research aims to comprehensively understand their influence. Subsequently, a method is proposed based on derivatives and high-pass filters to accurately detect eye blinks while minimizing the influence of simultaneous eye and head movements. The evaluation of the proposed method has demonstrated impressive performance, yielding an overall F1-score of 97.8% within distances ranging from 40 to 100cm. Furthermore, the results indicate the methods capability to detect eye blinks at distances up to 250cm, achieving an F1-score of 83.1%. These findings underscore the effectiveness of our approach in overcoming the challenges posed by various eye and weak head movements.**

***Keywords*—Eyeblink detection, EOG, FMCW radar, high-pass filter, derivative**

I. INTRODUCTION

Eye blinking, being a ubiquitous and innate human activity, serves as a vital indicator reflecting an individual's health or psychology status. Its significance extends to various domains, including the detection of drowsiness in long-distance driving [1, 2], the assessment of mental health in individuals with neurodegenerative disorders [3, 4], and the evaluation of concentration in learning settings [5]. Existing methods such as contact-based approaches using electrooculogram (EOG) [6, 7] and electroencephalogram (EEG) [8, 9] have limitations due to invasiveness and potential body reactions. On the other hand, contactless methods like camera-based [10, 11] face challenges related to privacy, lighting conditions, and line-of-sight issues. Additionally, sound-based approaches [12, 13] have limitations in providing high-resolution data.

The use of radar-based methods avoids light issues, reduces privacy concerns, and provides higher resolution compared to sound-based alternatives. Previous studies have explored radar technologies. As early as 2001, research had explored the feasibility of using radar to detect blinks [14]. Impulse radio ultra-wideband (IR-UWB) radar has been employed for blink behavioral monitoring during driving scenarios [15], as well as for detecting near-field intentional eyelid movement in the presence of stationary head and body motions [16]. Continuous wave (CW) radar has been utilized to identify driver blinks [2] and estimate blink duration by analyzing eyelid open-close patterns [17]. Furthermore, Frequency-modulated continuous wave (FMCW) radar has been employed in blink detection using the CEEMDAN algorithm [18] and for an interferometric approach to monitor both head movements and blinks [19]. Focusing on the feasibility of eye blink detection, they often overlooked the impact of other eye-related movements. Additionally, these studies reported results primarily in controlled environments, proposing solutions that do not effectively handle various eye movements. Notably, the detection range reported in previous work was limited to one meter in maximum.

These limitations originate from the inherent weak and special nature of the blink signal, with small amplitudes that pose difficulty for separation from radar noises. In addition, blink signals intertwine with reflections from other body parts, complicating accurate blink signal extraction. Beyond blinks, eye movements encompass changes in gaze direction, while subtle head movements induced by respiration and heartbeat further complicate blink detection. Furthermore, the varying degrees of eye closure in blinks contribute to the complexity of eye blink detection. In light of these challenges, the basic questions guiding this research are as follows: (1) What are the impacts of eye-related (eyeball, face, head) movements on radar reflected signals? (2) How can the impacts of these eye movements be mitigated? (3) What is the maximum range within which radar can possibly detect eyeblinks?

To address these questions, the impacts of various eye movements on radar return signals from the head region are first investigated through a variety of experiments and in-depth analysis in both time and frequency domains. Then, a signal processing pipeline is proposed, designed to detect eyeblinks while minimizing the influence of eye-related movements and noise such as breathing and heartbeat. A high-pass filter and a second-order derivative are used based on observations of the eyeblink's impact on radar signals and an evaluation of different algorithms. Finally, an extensive evaluation of the proposed processing pipeline is conducted, using both an electrooculogram (EOG) device and a camera as references. The evaluation includes different distances, blink types, and various impact factors to thoroughly assess the effectiveness and remaining issues of the proposed method.

In summary, this research makes three major contributions as the following.

- Unlike previous studies, the impact of each eye movement type on radar reflected signals is clarified through extensive experimentation and analysis.
- A method for eyeblink detection using radar signals is proposed, utilizing a high-pass filter and second-order derivative to mitigate the influence of eye-related movements.
- The performance evaluation of the proposed method achieved an overall F1-score of 97.8% in distances ranging from 40 to 100cm. Furthermore, notable

Supervisor: Prof. Jianhua Ma

performance was sustained at extended distances, yielding an F1-score of 83.1% at 250cm.

The remainder of this paper is organized as follows. Section II introduces EOG and eye blink features. Section III provides details about the radar-based eye blink detection method, while section IV presents various experiments and evaluation settings. In Section V, the comprehensive results of the performance evaluation are provided. Finally, Section VI gives a summary of this research with the important takeaways and discusses on important issues for future work.

II. Electrooculography and Eye Blink Features

In this section, the basic principle of EOG and the EOG device used are presented, along with a description of blink features and their characteristics in EOG signals.

A. *EOG Principles and Devise*

EOG signals are generated based on the inherent electrical differences within the eye, primarily resulting from variations in the eye's structural composition. These potential differences arise due to the distinct electrical properties of the cornea and the retina. As the eye moves within its socket or orbit, these potential differences change in orientation, creating dynamic electrical signals. Electrodes strategically placed around the eyes capture these changes in voltage, resulting in EOG waveforms that reflect eye movements, including blinks and changes in gaze direction.

A small analog front-end (AFE) bioelectric signal acquisition board, BioAmp EXG Pill [20], was used for the research. The EOG board was connected to the M5stick-C, which transferred the data to the computer via Bluetooth. The EOG device collects electrical signals through three electrodes attached to the skin. The electrodes are located above the right eye, below the right eye, and under the right ear. Fig. 1 shows the EOG device and electrode placement.

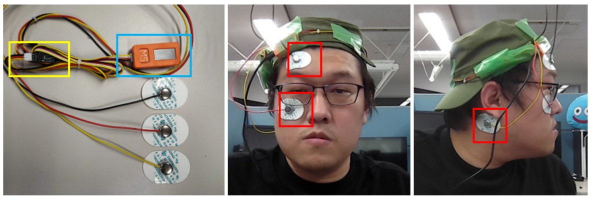

Fig. 1. EOG device (yellow - BioAmp, blue - M5strict-C and red - electrode)

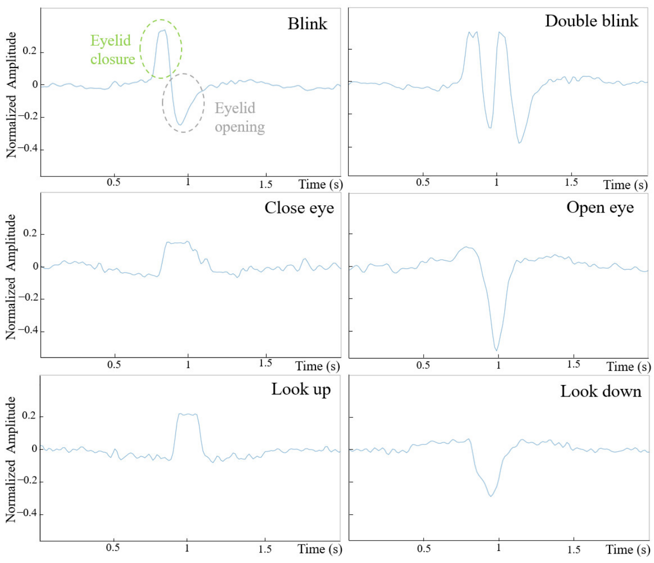

Fig. 2. EOG signals in different eye behaviors

B. *Eye Blink Features*

Slight fluctuations of the eyeballs are also visible in the EOG signal. Experiments were conducted on various eye behaviors in EOG signals, and typical eye behavioral signals are depicted in Fig. 2. When blinking, the EOG waveform appears as a peak and a trough. When double blinking, it is shown as two sets of continuous peaks and troughs. When looking up and to the left, there is only one peak, while looking down and to the right, there is only one trough. Also, when the eyes are closed only, the signal is presented as separate peaks and when the eyes are open, as separate troughs. A single blink behavior can be viewed as a combination of eye closing and eye opening at a very short time interval, and thus its waveform is consistent with the waveforms of the combined eye closing and eye opening.

Not only are there multiple eye movements, but there are also multiple types of blinks. Blinks are categorized basically into complete and incomplete ones. The incomplete blinks are further categorized into two types, one in which the eyes are closed no more than 50% during blink and the other in which the eyes are closed more than 50%, as shown in Fig. 3.

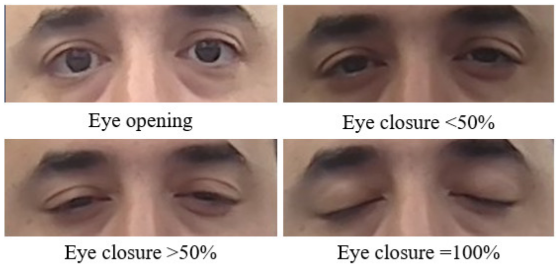

Fig. 3. Different eye closure levels of complete and incomplete blinks

Detecting incomplete blinks from the EOG signal is also a challenge, especially blinks below 50% closure, because their lid movements are much weak and can be easily confused with other movements or noise, as shown in Fig. 4.

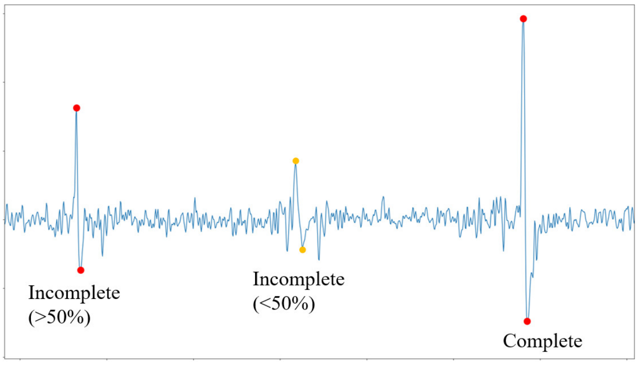

Fig. 4. EOG signal with incomplete and complete blinks

III. FMCW Radar Based Blink Detection Process

This section describes the blink monitoring pipeline based on FMCW radar. Based on the blink characteristics and its features in the radar signal, the following blink monitoring pipeline is used as shown in Fig. 5. It consists of three stages: blink-included signal acquisition, blink signal separation and reproduction, and blink event identification.

A. *Blink-included Signal Acquisition*

In the blink-included signal acquisition step, the raw data from radar goes through three stages that enables the correct extraction of the signal containing the eye blink information.

The three stages are clutter removal, eye range bin selection, and magnitude signal extraction.

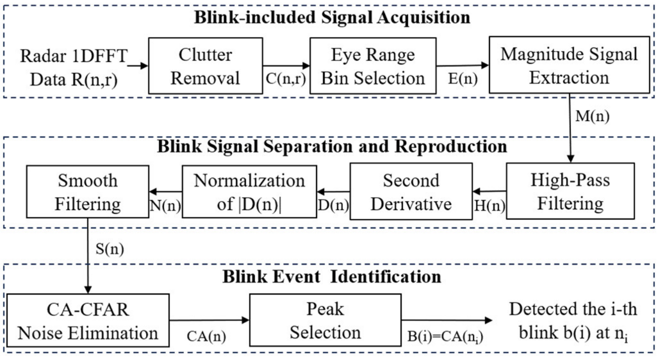

Fig. 5. FMCW radar based blink detection pipeline

Radar 1DFFT data is typically divided into discrete distance intervals known as "range bins". The 1DFFT signal includes reflection signals from static objects (furniture, walls, etc.) in the experimental environment. The use of clutter removal reduces the effect of these reflected signals. A widely used method is employed for this purpose, which involves subtracting the average value of each bin in the entire time series, as illustrated in Equation (1).

$$C(n,r) = R(n,r) - \frac{1}{T}\sum_{n=1}^{T} R(n,r) \qquad (1)$$

where $C(n,r)$ is the range bin signal after clutter removal, $R(n,r)$ is the raw radar signal, n is time samples index, r is the range bin index, and T is the number of time samples.

To select the correct range bin, the absolute value of $C(n,r)$ is computed and the argmax function is applied to obtain the maximum power bin index value for each sample point, resulting in the range bin $d(n)$, shown in Equation (2). The frequency of occurrence of each bin index is then recorded and the maximum value N is selected to represent the index value of the range bin in which the target is located, as shown in Equation (3).

$$d(n) = argmax(|C(n,r)|) \qquad (2)$$

$$N = mode\big(d(n)\big) \qquad (3)$$

$E(n)$ represents the signal in the bin where the blink signal is located, as shown in Equation (4).

$$E(n) = C(n,N) \qquad (4)$$

The eye blink signal $M(n)$ is contained in the magnitude part of the signal $E(n)$, as shown in Fig. 6, and obtained following Equation (5).

$$M(n) = abs\big(E(n)\big) \qquad (5)$$

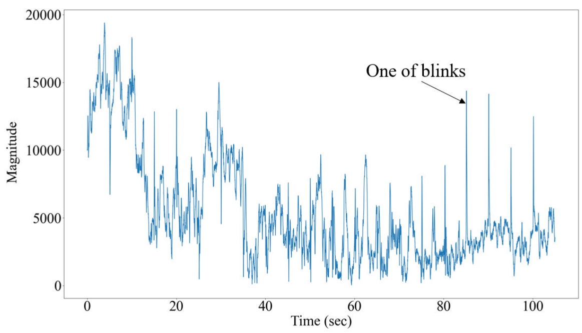

Fig. 6. Magnitude signal with blinks

B. Blink Signal Separation and Reproduction

In the blink signal separation and reproduction stage, there are four functional units, high-pass filtering, second derivative, normalization and smooth filtering.

Since the obtained magnitude signal contains not only the blink signal but also low-frequency noise, a Butterworth high-pass filter is used to remove the low-frequency noise and the slower motion signal, as show in Equation (6).

$$H(n) = \sum_{k=0}^{m} b_k M(n-k) - \sum_{k=1}^{m} a_k H(n-k) \qquad (6)$$

where $H(n)$ is the result of the magnitude signal passing through the high-pass filter, m is the order of the filter, and a_k and b_k are the coefficients of the filter, calculated using the Scipy.signal.butter function and based on the filter order and cutoff frequency. Fig. 7 shows the effect of the high-pass filter.

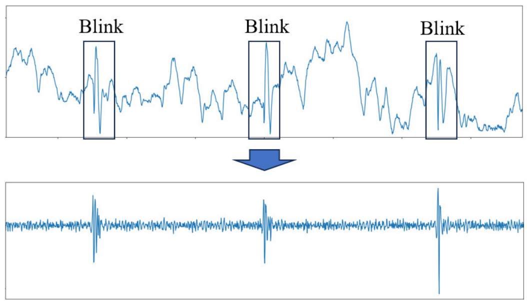

Fig. 7. Signals before and after high-pass filter

Then the blink signal is enhanced by taking two derivatives of $H(n)$ to obtain the second-order derivative $D(n)$, as shown in Equation (7). Additionally, the use of the second-order derivative can help eliminate false detections caused by weak eye movements, such as gaze changes.

$$D(n) = \frac{d^2H(n)}{dn^2} \qquad (7)$$

The signal is then normalized, as shown in Equation (8), to facilitate the blink detection part of the next step.

$$N(n) = \frac{|D(n)|}{\max\big(D(n)\big)} \qquad (8)$$

The Savitzky-Golay filter [21] is utilized for signal smoothing and to eliminate insignificant peaks. Following the normalization of the magnitude signal $N(n)$, the Savitzky-Golay filter is applied twice to obtain the smoother signal $S(n)$. The smoothed signal is depicted in Fig. 8.

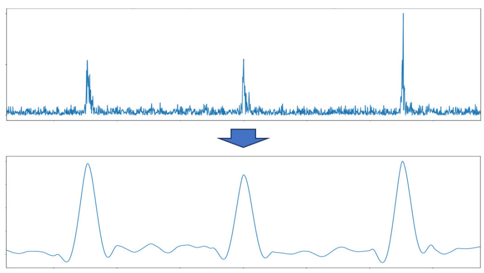

Fig. 8. Signals before and after smoothing filter

C. Blink Event Identification

The Cell Averaging Constant False Alarm Rate (CA-CFAR) [22] is applied to enhance the visibility of the individual eye blink events, which is a method for detecting a target signal in background noise. In the CA-CFAR algorithm, the sampling point to be detected is called the detection cell, and there are X guard cells and Y reference cells both before and after the detection cell. The sequence formed by the forward reference cells is $CF_{r1}(k)$ and the sequence formed by the backward reference cells is $CF_{r2}(k)$. The sampled values of all reference cells are averaged as an estimate of the power level of the background, denoted as B, as shown in Equation (9).

$$B = \frac{1}{2Y}\left(\sum_{i=1}^{Y} CF_{r1}(k) + \sum_{i=1}^{Y} CF_{r2}(k)\right) \tag{9}$$

The threshold T for the detection cell is determined as follows:

$$T = \alpha B \tag{10}$$

where α is the threshold product factor. When the power intensity of the detection cell is greater than or equal to the threshold, the power intensity is retained. If it is lower than the threshold, the power intensity is set to 0:

$$CA(n) = \begin{cases} 0, S(n) < T \\ S(n), S(n) \geq T \end{cases} \tag{11}$$

Since the threshold for each detection cell is determined by the sampling points around it, our threshold is dynamic. This approach also mitigates the impact of normalization special values. Fig. 9 illustrates the dynamic threshold and results for CA-CFAR. Finally, the blinks are counted using peak finding and the time index point at which the peak is located is recorded as the time sequence of blinks $b(i)$.

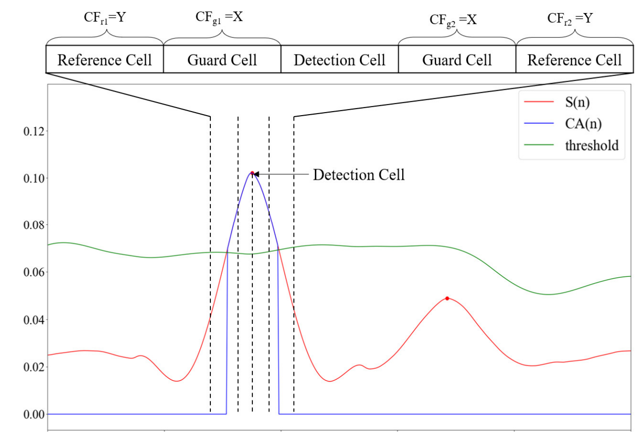

Fig. 9. CA-CFAR dynamic threshold (green) and output (blue)

IV. Radar Setup and Experiment Protocol

This section describes the setup and parameters of the radar used. In addition, the experimental environment and the specific requirements for the subjects in different experiments are described.

A. Radar Setup and Parameters

The TI-IWR1843BOOST [23] and an acquisition board DCA1000EVM [24] are used to acquire the raw data, as shown in Fig. 10. The acquisition frequency is 100 frames per second. The specialized mmWave Studio software is used to control the radar and set the parameters, which are shown in Table I. The data is transferred via ethernet interface to the laptop equipped with an NVIDIA RTX4080 GPU, 32GB RAM, and a 13th Gen Intel (R) Core (TM) i9-13980HX with 2.20 GHz CPU.

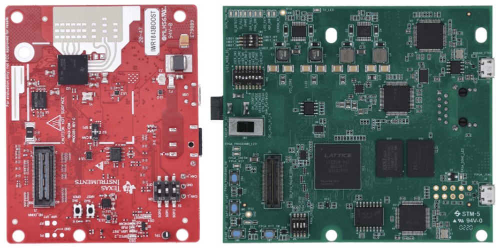

Fig. 10. IWR1843BOOST (left) and DCA1000EVM (right)

TABLE I. Radar Parameters Used in Experiments

Parameter	Value	Unit
Frequency	77-80.6	GHz
Frame period	10	ms
Idle time	10	µs
Frequency slope	29.982	MHz/µs
Chirp end time	120	µs
ADC start time	6	µs
ADC samples per chirp	256	-
ADC sampling frequency	2500	ksps

B. Experiment Setup and Protocal

This subsection provides the detailed description of the specific experimental environment and the experimental design for both controlled and impact experiments. In all experiments, the subjects wear EOG devices, which transmit data to the computer via Bluetooth.

1) Controlled Experiments

The controlled experiments are categorized into three cases: complete blinking experiment, incomplete blinking experiment, and blink detectable limit distance experiment, as shown in Table II. In these controlled experiments, the subjects were required to maintain their body still and gaze straight at the radar board, with the distance set separately for each experiment. The experimental environment is depicted in Fig. 11. During the experiment, the subjects are prompted to blink through a computer-generated beep sound produced at a frequency of once every 5 seconds. In the complete blink and detectable limit experiments, the subjects performed a complete blink when they hear the beep sound, while in the incomplete blink experiment, they perform an incomplete blink. Head support was used in the detectable limit and incomplete blink experiments, as illustrated in Fig. 12.

In the complete blink experiment, there were ten subjects, each blinking 100 times at each of the four distances, for a total of 4000 blinks. In the incomplete blink experiment, there was one subject who performed 100 blinks at each of four distances. In the detectable limit experiment, there was one subject who did 40 blinks each in ten different situations.

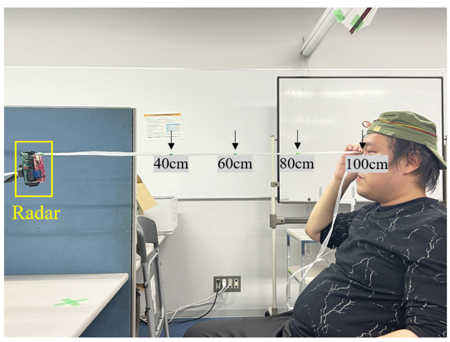

Fig. 11. Experimental environment in various distances

TABLE IV. ACCURACY ASSESSMENT EXPERIMENTS IN TERMS OF DISTANCE AND SUBJECT (%)

Subject	40cm			60cm			80cm			100cm		
	Pr	*Re*	*F1*	*Pr*	*Re*	*F1*	*Pr*	*Re*	*F1*	*Pr*	*Re*	*F1*
1	100	100	100	100	99	99.5	100	99	99.5	100	100	100
2	100	100	100	100	99	99.5	99	93.4	96.1	96	96	96
3	98	92.4	95.1	100	95.2	97.6	100	99	99.5	97	99	98
4	100	96.2	98	100	87	93	100	87	93	99	83	91
5	100	98	99	100	97.1	98.5	100	97.1	98.5	100	100	100
6	100	98	99	95	97.9	96.4	94	100	96.9	88	94.6	91.2
7	100	100	100	100	100	100	100	100	100	100	100	100
8	100	100	100	100	100	100	100	100	100	98	97	97.5
9	100	96.2	98	99	97	98	97	93.3	95.1	97	94.2	95.6
10	100	100	100	99	100	99.5	99	99	99	94	97.9	95.9
Avg.	99.8	98.1	98.9	99.3	97.2	98.2	98.9	96.8	97.8	96.9	96.2	96.5

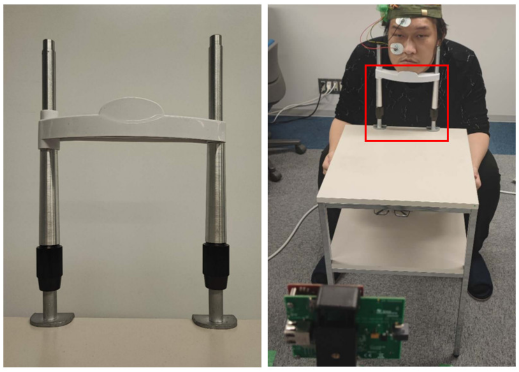

Fig. 12. Support (left) and experiment with head support (right)

TABLE II. CONTROLLED EXPERIMENTS IN DIFFERENT DISTANCES

Category	Distance
Complete blink	40, 60, 80, 100cm without support
Incomplete blink	40, 80, 100cm without support
	150cm with support
Detectable limit	150, 200, 250, 300cm without support
	150, 200, 250, 300, 350, 400cm with support

2) *Experiments with Impact Factors*

For the influence experiments, five types of experiments were conducted. The impact factors were blink interval, glasses, gaze, nearby people, and movement. The details of the experiments are shown in Table III. In the impact experiment, the subjects were always 60cm away from the radar, and complete blinks were performed following the computer, which produced a beep sound.

TABLE III. IMPACT EXPERIMENTS IN VARIOUS FACTORS

Impact factor	Condition
Blink interval	Open and close eye (1s, 5s)
	Double blink (0.3s, 1s)
Glasses	Without glasses
	With resin glasses, sunglasses and contact lens
Gaze	Up, down, left, right direction
	6 kinds of gaze changing
Nearby people	Sitting still, going straight, walking around
Movement	3 kinds of speed head swaying
	Face, head, body movement

The blink interval experiment was conducted by one subject and 50 actions were performed in each of the four conditions. The glasses experiment was set up with different numbers of subjects. Three subjects were set up to perform 40 blinks without glasses, wearing resin-based glasses, and wearing sunglasses. However, in the contact lens experiment, only one subject performed 100 blinks. In the experiment on the impact of gaze, nearby people, and movement, one subject was set up to perform 40 blinks in each of the different conditions.

V. BLINK DETECTION RESULTS AND IMPACTS

This section presents the results of several different experimental scenarios is presented to evaluate the accuracy and feasibility of the blink detection method. Then, the statistical results of the impact factors experiment, and further analysis of the impact factors are given. Precision (Pr), recall (Re), and F1-score (F1) are used as measures of our method's performance.

A. *Detection Results with Controlled Experiments*

In this subsection, the results for the close-range and complete blink condition are presented and the accuracy of the detection method is assessed. Subsequently, the detection results for incomplete blinks are analyzed. Finally, the maximum detectable distance that our method can achieve is examined, both with and without head support.

1) *Results of Complete Blink Detection*

Because blink detection is susceptible to various overlapping factors, the accuracy of our method was initially assessed under controlled experimental conditions that utilized beep sounds to prompt subjects to perform complete blinks. This evaluation involved a total of ten subjects, each tested at different distances, including 40, 60, 80, and 100cm, as presented in Table IV. Due to variations in the individual physical conditions of the subjects, some of them were unable to consistently blink every 5 seconds, leading to blinks occurring outside the predefined interval. Blinks that fell outside the specified criteria were excluded from the statistical results in Table IV.

Under complete blink conditions, our blink detection method achieved an overall F1-score exceeding 95% at various distances, and the individual blink detection accuracy levels for each subject exceeded 90%. However, due to individual differences among subjects, there was some variability in their accuracy. Subject 4 had a higher probability of false positive detections compared to other subjects, indicating a lower precision level. Further examination of the reference video used for the experiment revealed that subject 4 exhibited significant body movements during breathing, which introduced interference with the blink signal. On the other hand, subject 6 had a higher probability of missed detections compared to other subjects. Upon closer examination, it was observed that subject 6 had smaller eyes compared to other subjects, which may have contributed to missed detections.

The overall statistical results showed that with the increase in distance, the blink detection methods exhibited a decreasing trend in the three-evaluation metrics of precision, recall, and F1-score. This trend is expected because the reflected signal strength from the target decreases as the distance between the radar and the target increases. Furthermore, the blinking action is relatively weak and more susceptible to interference as the distance factor increases. However, even at the distance of 100cm, the F1-score remained at a high level of 96.5%, indicating that the blink detection method continued to perform effectively.

2) *Results of Incomplete Blink Detection*

Incomplete blinks are weaker and more challenging to control compared to complete blinks. Consequently, subjects were unable to consistently perform incomplete blinks at the same level across all blinks. To account for this variation, each blink within the experimental videos was counted to distinguish blinks with varying degrees of eye closure.

Table V shows statistical results for incomplete blinks. All complete blinks at all distances were successfully detected, but blinks with less than 50% eye closure could not be detected due to algorithmic thresholds and blinks that were too weak. 47 of 66 incomplete blinks are detected with more than 50% eye closure at 40cm with an accuracy of 71.2%. But after increasing distance, the accuracy was only 61.9% and 51.8% at 80 and 120cm, suggesting that incomplete blinks became very difficult to detect. Because of the lower accuracy, a head support is used at 150cm in the experiment to explore whether incomplete blinks could be detected at this distance. And in the 74 incomplete blinks where eye closure was more than 50%, 34 blinks are detected, with the accuracy of 45.9%. Since the magnitude signal strength of incomplete blinks is weak and comparable to the strength of some body noises, when lowering the detection threshold, the accuracy of detecting incomplete blinks increases, but the probability of false detection also increases. Thus, the detection of incomplete blinks is very challenging for our existing detection methods.

TABLE V. RESULTS UNDER DIFFERENT LEVELS OF EYE CLOSURE

Closure level \ Dis.		40cm	80cm	120cm	150cm
Complete	TP	15	3	9	3
	FP	0	0	0	0
	Pr (%)	100	100	100	100
Incomplete (> 50%)	TP	47	52	43	34
	FP	19	32	40	40
	Pr (%)	71.2	61.9	51.8	45.9
Incomplete (< 50%)	TP	0	0	0	0
	FP	19	13	8	14
	Pr (%)	0	0	0	0

3) *Result of Maximum Detctable Distance*

In this subsection, the maximum distance is explored at which a blink can be detected by our proposed method. Heartbeat and respiration can bring about slight head movements that may also affect our detection of blinks, so a head support is used to help explore the maximum distance at which a blink can be detected.

Table VI presents the results of the experiments conducted at various distances with and without head support. If the F1-score of the blink detection result falls below 50%, it is considered insufficient for blink detection under that specific condition. Consequently, there were no experiment results for distances of 350cm and 400cm without the use of head support. When head support was employed, the maximum distance at which a blink could be detected was 400cm, achieving an F1-score of 63.2%. Even when the radar was positioned at the distance of 300cm from the eye, the F1-score of the detection method still approached 90%. In addition, when head support was not used, the maximum distance at which a blink could be detected was 300cm, with the F1-score of 66.7%.

TABLE VI. RESULTS WITH AND WITHOUT SUPPORT (%)

Distance (cm)	With support			Without support		
	Pr	*Re*	*F1*	*Pr*	*Re*	*F1*
150	100	97.5	98.8	95	95	95
200	97.5	95.1	96.3	90	90	90
250	100	90.9	95.2	80	86.5	83.1
300	95	84.4	89.4	60	75	66.7
350	82.5	84.6	83.5	-	-	-
400	60	66.7	63.2	-	-	-

B. *Detection Impacts by Different Factors*

In this subsection, various factors are examined that influence the accuracy of radar-based blink detection. Impacts include blink interval, eyeglasses, gaze direction and changes, nearby person, and movements of the subject.

1) *Blink Interval Impact*

Most blinks consist of a single rapid closing and opening of the eyelid. However, special conditions may occur, such as eyelid closure held for a period of time before opening due to drowsiness, or rapid double blinks due to eyelid fatigue. The time between eyelid closure and opening and the time between double blinks are collectively referred to as the blink interval in this research. Table VII shows the experimental results at different blink interval. It is difficult to accurately detect this behavior when the eyelid closure and opening are not continuous. At intervals of 5 seconds and 1 second, the accuracy was only around 40%. When the interval between two blinks was 1 second, the accuracy was 90%. Inspection of the video and EOG revealed that the several double blinks in which missed detection occurred were the result of the subjects' failure to control the blink intervals, which were less than 1 second. When the interval between the two blinks was 0.3 second (the first blink was followed by the next blink without a pause), the accuracy was only 50%, meaning that all double blinks were detected as single blink. This experiment shows that the blink interval can have a large impact on blink detection.

TABLE VII. RESULTS FOR DIFFERENT BLINK INTERVALS

Condition	Interval (s)	TP	FP	Pr (%)
Open and close eye	5	19	31	38
	1	20	30	40
Double blink	1	45	5	90
	0.3	25	25	50

2) *Eyeglass Impact*

Wearing eyeglasses is common in modern life, so their potential effect on radar-based blink detection was investigated. Different types of glasses were used for the experiment since they are made of different materials. Table VIII compares the results of without glasses, with resin glasses, sunglasses, and contact lenses. The F1-score of the experiments without glasses and with resin glasses and sunglasses are almost the same and above 99%. This means that wearing resin glasses and sunglasses has almost no significant effect on our blink detection method. However, in the contact lens experiment, several false detections and missed detections were observed. From the reference video, it was determined that the subject had several incomplete blinks with no more than 50% eyelid closure during the experiment, resulting in missed detection. With other complete blinks, no missed detections occurred. Thus, contact lens wear had little effect on the blink detection method. Of course, these lenses are relatively common, and further research is needed to determine whether they would have a greater effect if they contained special materials.

TABLE VIII. RESULTS OF DIFFERENT GLASSES CONDITIONS (%)

Condition	Pr	Re	F1
Unworn glasses	99.2	100	99.6
Resin glasses	98.4	100	99.2
Sunglasses	100	98.4	99.2
Contact lens	96	97	96.5

3) *Gaze Impact*

Another influencing factor is gaze direction and gaze changes. In everyday life, it is impossible to maintain a constant gaze direction, and subjects occasionally change their gaze direction or blink while looking in directions other than straight ahead. Therefore, the aim is to investigate the impact of gaze and gaze changes on blink detection and identify the specific effects they may have on the methodology.

TABLE IX. RESULTS UNDER DIFFERENT GAZE DIRECTIONS (%)

Gaze direction \ Subject		1	2	3	Avg.
Up	Pr	100	100	100	100
	Re	100	100	100	100
	F1	100	100	100	100
Down	Pr	97.5	95	97.5	96.7
	Re	100	100	100	100
	F1	98.7	97.5	98.7	98.3
Right	Pr	100	97.5	100	99.2
	Re	100	100	100	100
	F1	100	98.7	100	99.6
Left	Pr	100	97.5	100	99.2
	Re	100	100	97.5	99.2
	F1	100	98.7	98.7	99.2

Changes in the magnitude signal reflect variations in the reflective properties of the target. Different gaze directions also lead to differences in the degree of eye opening. For instance, when looking upward, a larger portion of the eyeball is exposed compared to when looking downward. Consequently, blink events result in varying signal reflection intensities depending on the direction of gaze. When the gaze is directed upward, the eyelid opening is larger, and the change in the reflected area during a blink is more pronounced, making it easier to detect. Conversely, when the gaze is directed downward, the eyelid opening is smaller, resulting in lower magnitude power strength during blinking. Three subjects were observed blinking under different gaze directions, and the results were analyzed. Table IX presents the outcomes of blinking under various gaze directions. Blink detection achieved 100% accuracy when looking upward, while three subjects experienced missed detections when looking downward. This confirms the hypothesis that differences in gaze direction during blinking can impact blink detection.

On the other hand, changes in gaze direction can lead to eye actions that resemble blinks. For example, when the gaze direction changes from down to up, the eye opening becomes larger, which can influence blink detection. Therefore, the results of blink detection under various gaze changes in three subjects were analyzed to assess their impact. Table X presents the outcomes of blink detection under different gaze changes. In the five experimental conditions of down/left, down/right, up/right, up/left, and left/right, the F1-score for blink detection exceeded 98%, indicating that these types of visual transformations have minimal effect on blink detection. However, in the experimental condition of up/down, which involves a gaze transformation, the recall level decreased to 87.9%. This decrease suggests that some non-blink actions were mistakenly classified as blinks. Upon reviewing the experimental video, it was observed that most of the false detections occurred during the transformation of gaze from down to up. Therefore, among the different types of gaze changes, the up/down gaze changes have a notable effect on blink detection, while the other types of gaze changes have a lesser impact.

TABLE X. RESULTS DURING DIFFERENT GAZE CHANGES (%)

Gaze change \ Subject		1	2	3	Avg.
Down/up	Pr	92.5	100	97.5	96.7
	Re	84.1	95.2	84.8	87.9
	F1	88.1	97.6	90.7	92.1
Down/left	Pr	100	100	100	100
	Re	97.5	100	100	99.2
	F1	98.8	100	100	99.6
Down/right	Pr	100	100	97.5	99.2
	Re	100	100	97.5	99.2
	F1	100	100	97.5	99.2
Up/right	Pr	100	100	100	100
	Re	100	97.6	97.6	98.4
	F1	100	98.8	98.8	99.2
Up/left	Pr	97.5	97.5	100	98.3
	Re	97.5	100	100	99.2
	F1	97.5	98.7	100	98.7
Right/left	Pr	95	100	97.5	97.5
	Re	97.4	100	100	99.2
	F1	96.2	100	98.7	98.3

TABLE XI. RESULTS WITH NEARBY PEOPLE IMPACT (%)

Movement	Pr	Re	F1
Sit still	96.1	98	97
Go straight	100	72.5	84
Walk around	64	42.7	51.2

4) *Nearby People Impact*

This part investigates how blink detection is influenced when there are other people in close proximity to the subjects. The results, as shown in Table XI, indicate that blink detection remains largely unaffected when a nearby individual is sitting still next to the subject, with an F1-score value reaching 97%. However, when the nearby person walks back and forth in a straight line behind the subject, the F1-score value decreases to 84%, primarily due to an increase in false detections, resulting in a reduction in the recall value. The most significant impact occurs when the nearby individual moves around the subject, resulting in an F1-score value of only 50%, indicating that detecting a blink becomes challenging under these conditions.

5) Movement Impact

In previous experiments, it was observed that blink detection occasionally led to false detections and missed detections, particularly when the subject engaged in head or body movements during the experiment. Such movements had a detrimental effect on the accuracy of the detection method. Therefore, in this part, the impact of subject movements, including facial, head, and body movements, on the blink detection method is investigated.

Given the complexity of the movement types, the initial choice was to test weaker movements to understand the extent to which human movement affects the accuracy of blink detection. The simulation involved the subject looking at a computer screen while swaying the head from left to right. Table XII show the accuracy of blink detection for three speeds (very slow, slow, and moderate) of head swaying. When the head swaying is very slow, the F1-score can reach 95.2%, but as the head swaying speed increases, the F1-score decreases gradually to 76.9%. This suggests that even weaker movements can have a large impact on blink detection.

TABLE XII. RESULTS UNDER DIFFERENT SWAYING SPEED (%)

Sway speed	Pr	Re	F1
Very slow	100	90.9	95.2
Slow	100	75.8	86.2
Moderate	100	62.5	76.9

In previous studies, it was determined that if the magnitude of the movement was too large or the speed of the movement too fast, it became challenging to accurately count the blinks as valid results. Therefore, at present, our analysis focuses on examining the effects of different movements on blink signals. Due to the complexity of various forms of movement, including facial movements, head movements, and body movements, several representative movements have been selected to assess their impact. For facial movements, two movements have been chosen: frowning, which involves actions around the eyes, and twitching of the corners of the mouth, a more rapid movement similar to blinking. Regarding head movements, common movements such as nodding and tilting the head from side to side have been selected. For body movements, shaking and forward and backward movements have been chosen.

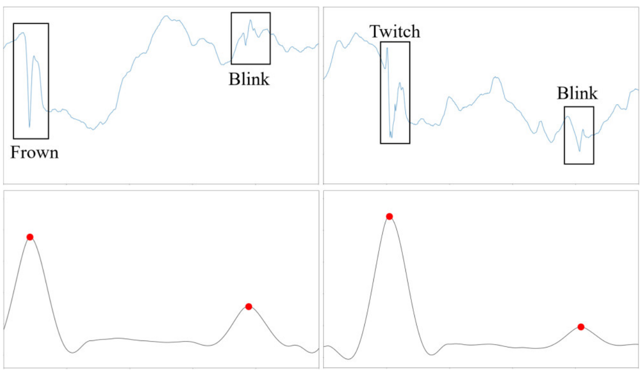

Fig. 13. Magnitude signals of blinking and face movements (upper) and detected results (lower)

Fig. 13 illustrates how the two motions, frowning and twitching of the corners of the mouth, compare with blinking in magnitude signal and are displayed in the blink detection results. Frowning and twitching of the corners of the mouth exhibit larger magnitude changes and sharper trends in the magnitude map when compared to blinking. These characteristics lead to noticeable wave peaks that are incorrectly detected as blinks during the blink detection process, resulting in false positives.

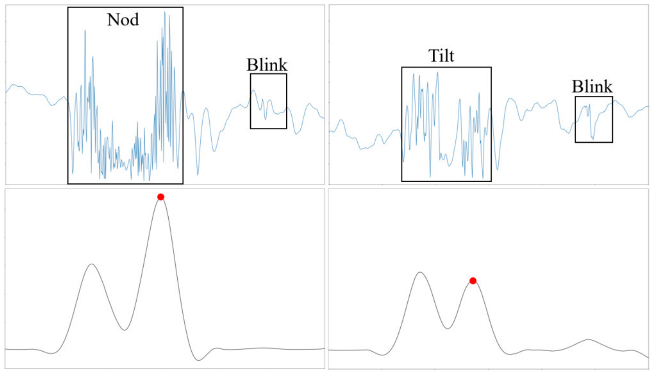

Fig. 14. Magnitude signals of blinking and head movements (upper) and detected results (lower)

Head movements cause more impact than face movements because when the head moves, it brings about a wider range of reflex fluctuations. Fig. 14 shows demonstrates the comparison of both head nodding and tilting head movements with blinking in terms of magnitude signals and shows their blink detection results. In the magnitude map, the magnitude signal generated by head movement exhibits significantly greater intensity than the blink signal. This discrepancy in magnitude intensity leads to a situation where the blink signal cannot be detected due to its relatively lower intensity, resulting in missed detections. In other words, when a blink occurred at the expected time point, no blink was detected at that time point. At the same time, due to the higher magnitude signal strength of the head movement, it will also be detected as a blink in the final detection session, resulting in false detection.

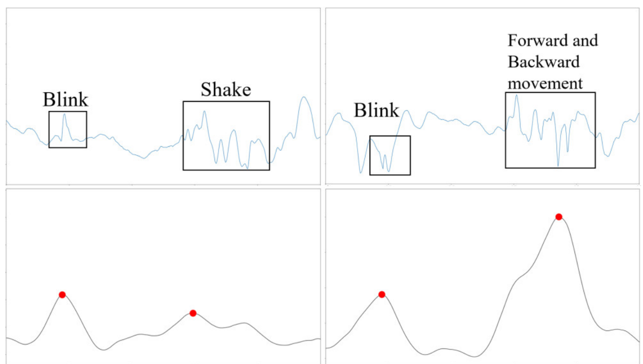

Fig. 15. Magnitude signals of blinking and body movements (upper) and detected results (lower)

Fig. 15 shows the magnitude signal changes and detection results from body shaking and forward and backward movement, where body motion produces significantly smaller magnitude signal changes relative to the effect of head motion. Therefore, the effect on blink detection is somewhat less, and although some false detections are generated, they usually do not cover the blink signal.

Among face movements, head movements, and body movements, head movements have the most significant impact on our blink detection. When a head movement occurs, it completely obscures the blink signal, resulting in a very low accuracy of blink detection. Facial and body movements produce some false detections, but do not completely mask the blink signal, resulting in more missed detections.

VI. Conclusion and Future Work

This research presents a novel blink detection method based on FMCW radar. The proposed method combines the high-pass filter and the second-order derivative for mitigation the effects of eye-related movements. The main results done in this research is summarized as follows. (1) The average F1-score has reached 97.8% for detecting complete blinks at the range 40 to 100cm. (2) The accuracies of detecting incomplete blinks with more than 50% eyelid closure are 71.2%, 51.8% and 45.0% at 40cm, 120cm, 150cm, respectively. And blinks with less than 50% eyelid closure are difficult to detect. These results indicate that the current detection method has limitations for detecting incomplete blinks. (3) This research has explored the detectable limit distance of a blink. Without using the head support, an F1-score of 83.1% could be achieved at the distance of 250cm and still 66.7% at 300cm. When the head support was used, the F1-score was 83.5% at 350cm. (4) The effects of individual subject factors on blink detection were analyzed, including blink interval, gaze, and movement. The blink interval has a large effect on blink detection. Looking down and changing gaze from up and down decrease the accuracy of blink detection. The face, head, and body movements also have the impacts on blink detection. Head movements have the greatest impact, masking blink features and causing large signal fluctuations, leading to missed and false detections. (5) The other impact factors including eyeglasses and nearby people existence were analyzed. Wearing different types of glasses has almost no impact. Nearby people can interfere with blink detection. Generally, the closer nearby people are and the more they move, the less detection accuracy will be.

Various restrictions and issues remain in the current research. Because of the threshold setting, incomplete blinks could not be accurately detected, and most of the results were based on the condition of complete blinks. After using multiple filters and other signal processing methods, although the blink signal was enhanced, detailed blink information such as the exact start time, end time, and duration of the blink was almost lost. This is not conducive to a more in-depth study of blink-related rich features. In addition, although the proposed method excludes the effect of some subtle movements (eye movements, body fluctuations due to breath and heartbeat, etc.) on blink detection, the larger magnitude movements still have a very serious impact on detection. There is still a need to find a better way to separate the movement signal from the blink signal. In future research, more advanced techniques such as machine learning or deep learning will be used to further extract the patterns of the blink and reduce the information loss in the filter-based signal processing. The better techniques are expected to solve the problems in detecting incomplete blinks, allowing for more reliable and richer eyeblink detection in the future.

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