Expert Systems With Applications

Distracted driving recognition based on functional connectivity analysis between physiological signals and perinasal perspiration index

--Manuscript Draft--

Manuscript Number:	ESWA-D-22-04808R2
Article Type:	Full length article
Keywords:	Functional connectivity, driving distractions, physiological signals, facial thermal images
Abstract:	Automatic detection of distracted driving is essential to ensure safety of drivers. In this paper, a novel set of features were extracted from thermal and physiological signals in order to detect and recognize distraction of drivers. Thermal video data which measured the temperature of different areas of the face, heart rate, breathing rate and behavioural signals were used while various types of distractions including cognitive, emotional and sensory-motor were applied to the subjects. The proposed discriminator features were extracted by different functional connectivity methods between the perinasal perspiration extracted from thermal images of the face and physiological variables of heart rate and breathing rate. After feature extraction, binary classification methods were applied to detect the distractions. The results showed that using functional connectivity features significantly increases the accuracy of distraction detection system (99.16%). Hence, the proposed model significantly improved (P<0.001) the detection of distraction compared to previous studies. Furthermore, we used the same feature set to recognize different types of distractions by using three-class classifiers. The suggested methods distinguished three types of distractions with the best accuracy of 81.94% related to cognitive, sensory-motor distraction and no-distraction states. We also tried to discriminate two types of cognitive distractions, analytic and mathematical distractions. The recognition system classified two types of cognitive distractions with an accuracy of 91.78%. The results suggest that there is important and complementary information in the connectivity between facial temperature signals and physiological variables for distraction detection and recognition.

Cover Letter

Tarbiat Modares University
Faculty of Electrical and Computer Engineering

Ale-Ahmad High way
P.O.Box:14115-194
Tehran, I.R. IRAN
Tell: +98 21-82883992
Fax: +98 21-82884325
www.modares.ac.ir/ece

October 09, 2022

Dear D. Binshan Lin,

Thank you for your consideration of our manuscript entitled “Distracted driving recognition based on functional connectivity analysis between physiological signals and perinasal perspiration index”. We have modified the manuscript according to the editorial comments and reviewers' comments. The point-to-point responses are included in the attached file which is named “Detailed Response to Reviewers “. For better tracking the corrections, we enclosed two files: “Revised manuscript” and “Highlighted”. The highlights of our study are written in the file named "Highlights" according to the Highlights guidelines.

In "Detailed Response to Reviewers", the questions are in brown and the answers are in black. The sections added to the article are displayed in blue and the deleted sections are displayed in red. In the "Highlighted" file, the changes related to the first reviewer's comments are shown in yellow and the changes related to the second reviewer's comments are shown in green. It should be noted that the items related to both reviewers' comments are highlighted in cyan.

We appreciate the time and effort that you and the reviewers dedicated to providing feedback about our manuscript and are grateful for the insightful comments which made valuable improvements to our paper.

Yours sincerely,

Zahra Bahmani

Zahra Bahmani, Ph.D.

Assistant Professor, Department of Electrical and Computer Engineering, Biomedical Engineering Group, Tarbiat Modares University

+98 (21) 82884992, email: z.bahmani@modares.ac.ir

In the name of God

Detailed Response to Reviewers

Section#1:

a.

As Editor-in-Chief, I'm writing this editorial decision letter on your paper submission ESWA-D-22-04808. If you are interested in submitting a revised version, please read through this entire editorial decision letter carefully and take all actions seriously in order to avoid any delay in the review process of your revised manuscript submission. You need to upload a 'Detailed Response to Reviewers' in the EM system with the following sections while submitting the revised manuscript. Please note that the Required Sections (Section #1 - a & b, Section #2 - a & b, Section #3 - a & b) with specific Compliance Requirements (stated in this editorial decision letter) must be clearly labeled and included in the 'Detailed Response to Reviewers.' The Required Sections must be clearly placed before the revised manuscript. NOTE: Section #1-(a) MUST contain the COMPLETE text covered in this email letter from Editor-in-Chief, rather than just only the first paragraph of this email letter from Editor-in-Chief. Please note that we will NOT admit any revised manuscript submission for further review if any of the Required Sections (i.e., Section #1 – a & b, Section #2 – a & b, Section #3 – a & b) is incomplete or any non-compliance of the ESWA authors' guidelines in the PDF file of the revised manuscript that you approve in EM system. So, you need to take both (1) Required Sections and (2) Compliance Requirements seriously to avoid any delay in the review process of your revised manuscript. The font size of the Required Sections should be consistent and readable. The Required Sections must be placed in the order listed as followings:

REQUIRED SECTIONS:

Section #1: a) and b)

a. Including the entire editorial decision letter (i.e., complete text covered in this email letter) from Editor-in-Chief, and

b. Including your responses to Editor-in-Chief.

Section #2: a) and b)

a. Including the entire Editorial Comments made by the Associate Editor, and

b. Including your Point-to-Point responses to the Associate Editor.

Section #3: a) and b)

a. Including the entire comments made by the Reviewers, and

b. Including your Point-to-Point responses to the Reviewers. Your Point-to-Point responses should be grouped by reviewers.

COMPLIANCE REQUIREMENTS:

In addition, please note that prior to admitting the revised submission to the next rigorous review process, all paper submissions must completely comply with ESWA Guide for Authors (see details at https://www.elsevier.com/journals/expert-systems-with-applications/0957-4174/guide-for-authors). These include at least the following Compliance Requirements:

A) Authorship policies - Please also note that ESWA takes authorship very seriously and all paper submissions MUST completely comply with all of the following three policies on authorship (clearly stated in the questionnaire responses in EM system) prior to a rigorous peer review process:

A)-1: The corresponding author needs to enter the full names, full affiliation with country and email address of every contributing author in EM online system. It is also mandatory that every contributing coauthor must be listed in EM at submission.

A)-2: It is mandatory that the full names, full affiliation with country and email address of every contributing author must be included in title (authorship) page of the manuscript. The first page of the manuscript should contain the title of the paper, and the full name, full affiliation with country and email address of every contributing author. The second page of the manuscript should begin with the paper abstract. Note that cover letter is not title (authorship) page.

A)-3: The authorship information in EM system must be consistent with the authorship information on the title (authorship) page of the manuscript.

B) Guidelines of reference style and reference list – Citations in the text should follow the referencing style used by the American Psychological Association (APA).

B)-1: Reference Style: Citations in the text should follow the referencing style used by the American Psychological Association. You are referred to the Publication Manual of the American

Psychological Association, Sixth Edition, ISBN 978-1-4338-0561-5. APA's in-text citations require the author's last name and the year of publication. You should cite publications in the text, for example, (Smith, 2020). However, you should not use [Smith, 2020]. Note: There should be no [1], [2], [3], etc in your manuscript.

B)-2: Reference List:

References should be arranged first alphabetically by the surname of the first author followed by initials of the author's given name, and then further sorted chronologically if necessary. More than one reference from the same author(s) in the same year must be identified by the letters 'a', 'b', 'c', etc., placed after the year of publication. For example, Van der Geer, J., Hanraads, J. A. J., & Lupton, R. A. (2010). The art of writing a scientific article. Journal of Scientific Communications, 163, 51–59. https://doi.org/10.1016/j.Sc.2010.00372. Note: There should be no [1], [2], [3], etc in your references list.

C) Highlights guidelines – There should be a maximum of 85 characters, including spaces, per Highlight in the Highlights section. Please kindly read this guideline carefully - the guideline does NOT say there should be a maximum of 85 words per Highlight. It says there should be a maximum of 85 characters per Highlight. As examples, the word "impact" consists of 6 characters; the word "significance" consists of 12 characters. Only include 3 to 5 Highlights. Minimum number is 3, and maximum number is 5.

NOTE: Your paper submission will be returned to authors and will NOT be admitted to further review if the revised paper fails to completely comply with the ESWA Authorship policies, ESWA guidelines of reference style and reference list, Highlights guidelines. You need to take the Compliance Requirements seriously to avoid any delay in the review process of your revised manuscript.

To submit a Complete and Compliance revision, please go to https://www.editorialmanager.com/eswa/ and login as an Author.

Your username is: z.bahmani

If you need to retrieve password details, please go to:

https://www.editorialmanager.com/eswa/l.asp?i=1820128&l=UI8DK7ZA

On your Main Menu page is a folder entitled "Submissions Needing Revision". You will find your submission record there.

The submission deadline of revised version is October 9, 2022.

Look forward to receiving (1) your revised submission and (2) Required Sections (i.e., Section #1 – a & b, Section #2 – a & b, and Section #3 – a & b) with Compliance Requirements in 'Detailed Response to Reviewers.'

With kind regards,

Dr. Binshan Lin

BellSouth Professor

Editor-in-Chief, Expert Systems with Applications

Louisiana State University Shreveport

Email: Binshan.Lin@LSUS.edu

b.

Dear Dr. Binshan Lin,

Thank you for your consideration of our manuscript entitled "*Distracted driving recognition based on functional connectivity analysis between physiological signals and perinasal perspiration index*". We have modified the manuscript according to the reviewer's comments in the Answer file which has been attached ("Detailed Response to Reviewers"). For better tracking the corrections, we enclosed two files: "Revised manuscript" and "Highlighted".

We checked "Compliance Requirements". We have complied with all "Authorship policies". "Guidelines of reference style" was carefully studied and "reference list" was updated according to the guidelines. We reviewed the "Highlights guidelines" and corrected related highlights which are written in the file named "Highlights".

In "Detailed Response to Reviewers", the questions are in brown and the answers are in black. The sections added to the manuscript are displayed in blue and the deleted sections are displayed in red. In the "Highlighted" file, the changes related to the first reviewer's comments are shown in yellow and the changes related to the second reviewer's comments are shown in green. It should be noted that the items related to both reviewers' comments are highlighted in cyan.

We appreciate the time and effort that you and the reviewers dedicated to providing feedback about our manuscript and are grateful for the insightful comments which made valuable improvements to our paper.

Yours sincerely,

Zahra Bahmani, Ph.D.

Assistant Professor, Department of Electrical and Computer Engineering, Biomedical Engineering Group, Tarbiat Modares University

+98 (21) 82884992, email: z.bahmani@modares.ac.ir

Section#2:

a.

Associate Editor's Editorial Comments:

Comment #1: If you are interested in submitting a revised version, please revise paper and provide very convincing point-to-point responses according to the comments raised by the reviewers. When you revise your submission, please highlight the changes you make in the manuscript by using colored text.

* Please note that you are not obliged to add suggested references by the reviewers. If you detect any abuse in the suggested literature, please do not hesitate to contact me.

Comment #2: Prior to the next review process, you need to completely comply with

- ESWA authorship policies,
- ESWA guidelines of reference style and reference list, and
- highlight guidelines.

Any non-compliance paper submission will be returned to authors. Please do take the Compliance Requirements seriously to avoid any delay in the review process of your revised manuscript.

Comment #3: Prior to the next review process, your submission needs to include each of the “Required Sections.” The Required Sections must be placed in the order listed: Section #1 – a, Section #1-b, Section #2-a, Section #2-b, Section #3-a, and Section #3-b.

* Note that Section #1- a MUST contain the COMPLETE text covered in this email letter from Editor-in-Chief.

Your paper submission will be returned to authors and will NOT be admitted to further review if the revised paper submission is incomplete. So please take both (1) Required Sections and (2) Compliance Requirements seriously to avoid any delay in the review process of your revised manuscript.

b.

Answer to the comment #1:

We revised the manuscript and provided point-to-point responses according to the comments. In "Detailed Response to Reviewers" file, the point-to-point responses are included in which the questions are in brown and the answers are in black. The sections added to the manuscript are displayed in blue and the deleted sections are displayed in red.

We sent "Highlighted" file that highlights the changes made in the manuscript by using colored text. In the "Highlighted" file, the changes related to the first reviewer's comments are shown in yellow and the changes related to the second reviewer's comment are shown in green. It should be noted that the items related to both reviewers' comments are highlighted in cyan.

Answer to the comment #2:

We have complied "ESWA authorship policies". "ESWA guidelines of reference style" were checked and "reference list" was updated according to the guidelines. We reviewed the "Highlights guidelines" and corrected related highlights which are written in the file named "Highlights". We carefully checked "Compliance Requirements".

Answer to the comment #3:

The “Required Sections” were included and were placed in the ordered list in the "Detailed Response to Reviewers" file.

Thanks for your attention.

Section #3:

Answers to the reviewers' comments are as follows. The comments are in brown, our answers are in black. removed sentences are in red, added and modified sentences in the manuscript are in blue colors. For better tracking the corrections, we enclosed two files: "Manuscript" and "Highlighted". In the "Highlighted" file, the changes related to the first review's comment are shown in yellow and the changes related to the second review's comment are shown in green. It should be noted that the items related to both reviews' comments are highlighted in cyan.

Reviewer 1:

Thanks for your precise comments.

Q.1. The indentation format of the whole article is not uniform:
For example, the contents in sections 2.5, 3.1.3 and 3.3 are different from those under the same level title. The author is expected to check the whole article and unify the indentation format of the article.

Ans.1. Thank you for pointing this out. We checked the whole manuscript and unified the indentation format of the manuscript.

Q.2. The conclusion can be more concise, directly point out the innovative methods and experiments of this study, and highlight the comparison between the final experimental results of this study and the current general experimental results. Other miscellaneous parts such as "we often hear... End someone's life." should be in the research significance or introduction.

Ans.2. We think this is an excellent suggestion. We rewrite conclusion and discussion section in order to make the innovation of the manuscript clearer and highlighted the comparison between the final experimental results of this study and the current general experimental results. The sentences " we often hear... End someone's life." were removed from this section.

Q.3. Strengthen the reference relationship between the chart and the paragraphs of the article, for example, figure 2, in the description of the article, does not directly give the guidance to the paragraphs explained in Figure 2.

Ans.3. Thanks for the reviewer's attention. The reference relationship between figures and tables are strengthened in the manuscript. The changed parts are as follows:

Section (2.2):
According to the fig. 2, some of the physiological and behavioral variables of drivers have been measured in the Simulator Study 1 dataset (Taamneh, 2017).

Section 3:
As shown in Table 2, all classical (statistical and structural) features of the PP signal passed the criteria of filter and considered as features for classification training.

Section (3.1.1):
In this part we used 44 classic features of all variables (BR, HR, LO, PP) and trained a Bayesian classifier as distraction detection model. As a result, As shown in Table 3, the ACC of detection between distracted and normal driving was 59.40% ($ACC_{distracted\ vs.\ normal} = 59.40\%, AUC_{distracted\ vs.\ normal} = 0.64, F1_{distracted\ vs.\ normal} = 0.28$).

Section (3.1.3):
The purpose of this analysis, as shown in table 4, was to distinguish the most useful and informative pair of signals mentioned in the distraction detection system.

Fig. 7 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on BR_PP variables.

Fig. 8 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on HR_PP variables.

Fig. 9 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on LO_PP variables.

Section (3.2.1):

As shown in Table 5, All classic and connectivity features were extracted from three pairs of PP-HR, PP-BR, and PP-LO signals.

Section (3.2.2):

AS shown in Table 6, we obtained 91.78% ACC of recognition among CD_AQ, CD_MQ, ND ($ACC_{ND,CD-AQ,CD-MQ} = 91.78\%, F1_{ND,CD-AQ,CD-MQ} = 0.93$).

Q.4. The experimental methods, tasks and datasets of this study refer to "taamneh et al., 2017 and Pavlidis et al., 2016". After adding the innovation points of this paper, can the experimental methods, tasks and datasets meet the needs of this study? If so, what is the significance of this study?

Ans.4. Thank you.

We used the driving simulator data-set recorded by Pavlidis Group. This data-set has the comprehensiveness of the number of subjects and different kinds of recorded signals. The data-set includes different physiological, behavioral and thermal signals of the driver in different sessions of mental and physical distraction. We achieved a higher level of accuracy to detect the driver's distraction from the normal state compared to recent studies. Our innovation was in the functional connectivity features between physiological and thermal signals that we used. We used these features for the first time, which led to higher accuracy for general distraction detection. On the other hand, for the first time, we categorized different types of distraction into 3 and 4 classes.

We added these sentences to clarify the subject.

Section (2.1):

Simulator study 1 dataset was obtained by Pavlidis group. We will briefly explain about the task and data. For complete details of the task and dataset, refer to the following references Taamneh et al., 2017 and Pavlidis et al., 2016.

Section (2.5):

We used connectivity features between physiological, thermal and behavioral signals in order to detect and recognize distraction for the first time in this field. No one has used these types of features in the previous studies.

Section (3.4):

we used these connectivity features for the first time, which led to higher accuracy of distraction detection. We achieved a higher level of accuracy to detect the driver's distraction from the normal state than recent studies.

Q.5. This study refers to 21 Chinese and foreign literatures, and the application rate of literatures in the past three years is 28.57%. Among the references, there are even references in 2009. The algorithm application literature is very timely. It is hoped that more literatures in the past five years will be added to support the feasibility of this study.

Ans.5. Thank you for this suggestion.

The reference in 2009 is a basic reference for explaining cross-correlation. This article is not about distraction detection systems. In this article, only the cross-correlation method has been investigated, which we used as one of the connectivity features. So, we preferred to keep it. However, we added recent studies in the field and removed some older ones as follows:

Added studies:

Dey, A. K., Goel, B., & Chellappan, S. (2021). Context-driven detection of distracted driving using images from in-car cameras. Internet of Things, 14, 100380.

Alzubi, J. A., Jain, R., Alzubi, O., Thareja, A., & Upadhyay, Y. (2022). Distracted driver detection using compressed energy efficient convolutional neural network. Journal of Intelligent & Fuzzy Systems, 42(2), 1253-1265.

Wang, X., Xu, R., Zhang, S., Zhuang, Y., & Wang, Y. (2022). Driver distraction detection based on vehicle dynamics using naturalistic driving data. Transportation research part C: emerging technologies, 136, 103561.

Ma, Y., Gu, G., Yin, B., Qi, S., Chen, K., & Chan, C. (2022). Support vector machines for the identification of real-time driving distraction using in-vehicle information systems. Journal of Transportation Safety & Security, 14(2), 232-255.

Fan, C., Peng, Y., Peng, S., Zhang, H., Wu, Y., & Kwong, S. (2021). Detection of train driver fatigue and distraction based on forehead EEG: a time-series ensemble learning method. IEEE Transactions on Intelligent Transportation Systems.

Li, G., Yan, W., Li, S., Qu, X., Chu, W., & Cao, D. (2021). A temporal-spatial deep learning approach for driver distraction detection based on EEG signals. IEEE Transactions on Automation Science and Engineering.

Liang, J., Zhu, H., Zhang, E., & Zhang, J. (2022). Stargazer: A transformer-based driver action detection system for intelligent transportation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 3160-3167).

Deleted references:

" Mohd, M. N. H., Kashima, M., Sato, K., & Watanabe, M. (2015). Mental stress recognition based on non-invasive and non-contact measurement from stereo thermal and visible sensors. International Journal of Affective Engineering, 14(1), 9-17."

" Ooi, J. S. K., Ahmad, S. A., Chong, Y. Z., Ali, S. H. M., Ai, G., & Wagatsuma, H. (2016, December). Driver emotion recognition framework based on electrodermal activity measurements during simulated driving conditions. In 2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES) (pp. 365-369). IEEE.".

We also added the following paragraph in the introduction section:

As mentioned, distraction detection systems should be improved in terms of system's performance and consideration of different distraction factors. Mostly, studies in the field focused on, physical distraction factors (Wang, 2022), however, mental (emotional and cognitive) distraction factors are as dangerous as physical distractions (sensory-motor). So, introducing general distraction systems with high performances is necessary. Among recent studies on Pavlidis simulator dataset (Panagopoulos, 2019), the best accuracy was 78.36% for detecting distraction including all factors. Besides, distraction recognition systems should be considered as a new module to these systems. Using distraction recognition systems, the types of distraction factors are also predicted. Distraction factors can be handled differently in real applications for drivers.

The following sentences are added:

The behavioral signals can be used for distraction detection (Ma, 2022). Besides, Physiological signals, visible and non-visible videos and brain signals included indicator indexes of distraction.

Q.6. When identifying the distracted state and the normal state, the accuracy rate of this study has reached 99.16%, but when identifying different types of distraction, especially the multi distracted type, the accuracy rate of this study is 66.42% and 63.39%, which is far lower than most of the existing research results. Therefore, can we consider deleting this part in the conclusion to highlight the research results of the identification of the distracted state and the normal state.

Ans.6. Thank you for pointing this out. According to the reviewer's comment, we removed this part from the conclusion and rewrite conclusion and discussion section in order to make the innovation of the manuscript clearer and highlighted the significant research results.

Q.7. In Section 2.2, if PP of all subjects cannot be obtained due to non-resistant factors, is it necessary to add a control group without PP in this study, and only effective data of 58 subjects, which is not representative.

Ans.7. Thank you.

One of the novelties of this study is the use of connectivity between PP (as a main signal) and other signals for improvement of driver's distraction detection. Therefore, measuring the connectivity features without PP is out of scope of this research. If for some people it is not possible to extract the PP signal because of facial hair, it is possible to use the signals of other areas of the face extracted from thermal images such as the forehead area or areas around the eyes. This topic is also part of our future work.

Q.8. There is too much white space between the full text figure, table and text, and the spacing is not uniform: For example: Table 1, table 2, table 4, etc., FIG. 11 and FIG. 12, etc. the author is expected to check the whole article and revise it in accordance with the requirements of the journal.

Ans.8. We agree with the reviewer’s assessment.
We checked the whole manuscript and fixed the mentioned problem by deleting the white spaces between the figures, tables and text and unified them.

Reviewer 3:

1. The main objectives of this study and novelty point should be clearly discussed in detail.

Ans.1. We do agree with the reviewer’s assessment.
According to the reviewers’ comments, changes were made in the conclusion and discussion section in order to make the innovation of the manuscript clearer and discussed results clearly in details. The sentence " we often hear... End someone's life." was removed from this section.
Also, Sentences were added in the text of the manuscript in sections 2.5 and 3.4.

Section (2.5):

We used connectivity features between physiological, thermal and behavioral signals in order to detect and recognize distraction for the first time in this field. No one has used these types of features in the previous studies.

Section (3.4):

we used these connectivity features for the first time, which led to higher accuracy ACC of distraction detection. We achieved a higher level of accuracy ACC to detect the driver's distraction from the normal state than recent studies.

2. Make a literature review section clearly and then focus on the research issues and contributions, which are not made clear in this paper.

Ans.2. Thanks for the relevant comment. To make the literature review section clear, we added the following paragraph in the introduction section.

As mentioned, distraction detection systems should be improved in terms of system’s performance and consideration of different distraction factors. Mostly, studies in the field focused on, physical distraction factors (Wang, 2022), however, mental (emotional and cognitive) distraction factors are as dangerous as physical distractions (sensory-motor). So, introducing general distraction systems with high performances is necessary. Among recent studies on Pavlidis simulator dataset (Panagopoulos, 2019), the best accuracy was 78.36% for detecting distraction including all factors. Besides, distraction recognition systems should be considered as a new module to these systems. Using distraction recognition systems, the types of distraction factors are also predicted. Distraction factors can be handled differently in real applications for drivers.

We also reviewed recent studies and added new references in the introduction section. The following sentences are added.
The behavioral signals can be used for distraction detection (Ma, 2022). Besides, Physiological signals, visible and non-visible videos and brain signals included indicator indexes of distraction.

we added recent studies in the filed while removed some older ones as follows:

Added studies:

Dey, A. K., Goel, B., & Chellappan, S. (2021). Context-driven detection of distracted driving using images from in-car cameras. Internet of Things, 14, 100380.

Alzubi, J. A., Jain, R., Alzubi, O., Thareja, A., & Upadhyay, Y. (2022). Distracted driver detection using compressed energy efficient convolutional neural network. Journal of Intelligent & Fuzzy Systems, 42(2), 1253-1265.

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Li, G., Yan, W., Li, S., Qu, X., Chu, W., & Cao, D. (2021). A temporal-spatial deep learning approach for driver distraction detection based on EEG signals. IEEE Transactions on Automation Science and Engineering.

Liang, J., Zhu, H., Zhang, E., & Zhang, J. (2022). Stargazer: A transformer-based driver action detection system for intelligent transportation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 3160-3167).

3. In general, improvements related to the abstract, qualify of figures and equations presentation must be presented. Acronyms and variables in equations must be defined in

the manuscript. Some figures are with low resolution. Please verify it. Equations of the evaluated models could be presented. Note: Mathematical notations should be italicized.

Ans.3. Thank you for pointing this out. The abstract is rewritten and the novelties of the study are highlighted. We improved the quality of figures 3,5,6,7,8,9 and 12. We made some small changes to Figures 1 and 2. For Fig. 1 we removed "LOSO" and in Fig. 2 we put "HR" and "BR" together.

We changed the captions of figures and tables as follows:

Fig. 1:
Block diagram of the proposed method. LOSO: leave one subject out validation.

Fig. 3:
Three non-directional functional connectivity containing PP were used (PP-BR), (PP-HR) and (PP-LO). HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset. (color should be used for this figure in print)

Table 2:
Included sets of classic features which were used in this study. HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset.

Table 3.
Performance of Bayesian classification to detect driver distraction from normal case by using classic features and functional connectivity features. ACC: accuracy, AUC: area under the curve and F1: Fisher-measure.

Fig. 6:
Results of Bayesian classification to detect each distraction factor (CD=Cognitive Drive, ED=Emotional Drive and MD=sensory-Motor Drive) from ND (No-distracted Drive) using all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

Table 4:
Bayesian classification results of distraction detection using coupling variables. HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset.

Fig. 7:
Results of Bayesian classification for BR_PP as a paired connectivity variable with all classic and connectivity features. BR: Breathing rate, PP: Perinasal perspiration. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-

distracted Drive. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

Fig. 8.
Results of Bayesian classification for HR_PP as a pair of connectivity variable with all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***) HR: Heart rate, PP: Perinasal perspiration. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive (color should be used for this figure in print)

Fig. 9:
Results of Bayesian classification for LO_PP as a pair of connectivity variable with all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). PP: Perinasal perspiration and LO: Lane offset. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive (color should be used for this figure in print)

Table 5:
Results of three-class distraction recognition system. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive

Table 7:
Results of Bayesian classification to recognize types of distraction (four-classes). CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive
Fig. 12:
Comparison of distraction detection system based on Bayesian, KNN and SVM classifiers using all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

Table 8:
Comparison of driver distraction detection in previous studies with the proposed method. Factor 1: Physiological, 2: Behavioral and 3: Thermal signals. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive

Acronyms and variables in equations are completely defined in the manuscript and we showed them as follows:

Section 2.3:

As preprocessing, we used a within subject normalization method called Z-Score (Equation 1). In this method, we subtracted each sample (i) of signal (x) from the average of samples (μ) and divided it by standard deviation (S). This process was applied on each signal for each subject separately.

$$Z_{Score} = (x_i - \mu)/\ S \tag{1}$$

Section 2.5:

$$cov(x,y) = 1/(n-1)\sum_{i=1}^{n}(x_i - \mu_x)(y_i - \mu_y) \tag{2}$$

Equation 2 shows how the covariance (cov) of the two signals x, y is calculated from observations of each signal and the mean of the signals (μ_x, μ_y); n is the sample size and i is each sample of signals. It shows what happens to *y* with changes in *x*, and vice versa. The correlation is a normalized covariance with values between 1 and -1. The correlation between the two signals was calculated as the correlation coefficient (Equation 3).

$$\rho_{xy} = cov(x,y)/\sqrt{\sigma_x^2 * \sigma_y^2} \tag{3}$$

In this equation *cov (x, y)* is the covariance between two signals *x* and *y*. σ_x^2 and σ_y^2 are the variance of the two signals x and y, respectively. The correlation coefficient (ρ) between two variables (*x*, *y*) is the ability to predict the value of one variable from the other.

The Mathematical notations were updated in the whole text of manuscript.

4. Tables (4, 5, ...) with classification results: A full statistical analysis of the model results must be presented. Furthermore, a comparison of the evaluated models with state-of-art models must be presented based on cross-validation procedure (k-fold), performance measures and significance nonparametric tests.
   Authors could perform statistical tests (e.g. Friedman test + Posthoc Nemenyi test) to compare algorithms and discuss the results in the paper. Discussion of the results are not adequate and sufficient. Illustrate them very clearly and bring insights from them.

Ans.4. We think this is an excellent suggestion. We presented a full statistical analysis of the model results as follows:

After Table 2:

As shown in Table 2, all classical (statistical and structural) features of the PP signal passed the criteria of filter and considered as features for classification training.

Before table 3:

In this part we used 44 classic features of all variables (BR, HR, LO, PP) and trained a Bayesian classifier as distraction detection model. As shown in Table 3, the ACC of detection between distracted and normal driving was 59.40% ($ACC_{distracted\ vs.\ normal} = 59.40\%, AUC_{distracted\ vs.\ normal} = 0.64, F1_{distracted\ vs.\ normal} = 0.28$). After adding 18 functional connectivity features, the ACC of distraction detection reached 96.31% ($ACC_{distracted\ vs.\ normal} = 96.31\%, AUC_{distracted\ vs.\ normal} = 1, F1_{distracted\ vs.\ normal} = 0.96$).

After table 3:

In this case, more that 30% increase in ACC was obtained by using connectivity features. We used Wilcoxon signed rank test for investigating statistically significant differences of performance measurements between classic and total feature sets of table 3. There was statistically significant difference between ACC of classic features and ACC of total features ($P<0.001$). There was statistically significant difference between AUC of classic and total features ($P<0.001$), and there was statistically significant difference between F1 of classic features and F1 of total features ($P<0.001$). This analysis shows that, the performance of the distraction detection system after adding connectivity features significantly enhanced. These results indicate that new and complementary information exists in the connectivity between physiological, thermal and behavioral signals. The accuracy was calculated from the average accuracy of each test subject using leave one subject out cross validation.

After Fig. 5:

Fig. 5 shows the effectiveness of the functional connectivity features for each subject. All 58 subjects showed noticeable improvement in ACC of distraction detection.

After Fig. 6:

The results showed that the ED with the highest ACC and F1 is was the most detectable factor from the no-distraction mode.

We used Wilcoxon sign rank test for investigating significantly different between mental and physical distractions. There was statistically significant difference between ACC of ND_MD as the physical distractor and ND_ED as the mental distraction ($P<0.001$). Also, there were statistically significant difference between ND_MD as the physical distractor and ND_CD as the mental distraction ($P=0.015$). As a result, this connectivity feature set could detect mental distraction better than physical one.

After Fig. 4:

We investigated statistically significant difference among these the ACC of distraction detection system using BR-PP, HR-PP and LO-PP pairs of signals with non-parametric Friedman test. There were the significant difference among ACC of BR_PP, HR_PP and LO_PP (ACC_(BR-PP, distracted vs. ND)=93.72%±3.0074,ACC_(HR-PP, distracted vs. ND)=92.13±0.9081,ACC_(LO-PP, distracted vs. ND)=60.02±5.3140*10^(-5), $P<0.001$). Using Friedman test, there was a significant difference among the AUC of these three groups of signals ($P<0.001$). Also, there was a significant difference among the F1 of these three groups of signals ($P<0.001$). For calculating the significant difference between two of them, we used non-parametric Posthoc Nemenyi test. The ACC ($P<0.001$) and F1 ($P<0.001$) of BR_PP and LO_PP were significantly different and the ACC ($P<0.001$) and F1 ($P<0.001$) of HR_PP and LO_PP were also significantly different. But the ACC ($P=0.742$) and F1($P=0.301$) of BR_PP and HR_PP wasn't significantly different. The AUC of BR_PP and LO_PP ($P<0.001$), HR_PP and LO_PP ($P<0.001$) was significantly different. Also, the AUC of BR_PP and HR_PP was significantly different ($P<0.001$). The results showed that the connectivity between two signals of BR and PP was the most informative pair to detect two classes of driver distraction

After Fig. 7:

Fig. 7 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for compression. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There wasn't any significant difference between ACC of the system for classifying MD as physical distractor and CD as mental distractor from normal state in this case ($P=0.439$). There was significant difference between ACC of the system for classifying MD as physical distractor and ED as mental distractor from normal state in this case ($P<0.001$).

After Fig. 8:

Fig. 8 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for compression. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There was significant difference between system performances for classifying ED as mental and MD as physical distractions from normal state in this case ($P<0.01$). There was significant difference between system performances for classifying CD as mental and MD as physical distractions from normal state in this case ($P<0.05$).

After Fig. 9:

Fig. 9 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for compression. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There was significant difference between system performances for classifying ED as mental and MD as physical distractions from normal state in this case ($P<0.05$). There was significant difference between system performances for classifying CD as mental and MD as physical distractions from normal state in this case ($P<0.05$).

As a result of Fig. 7, Fig. 8 and Fig. 9 ACC of the distraction detection system was the most for discrimination between ND and CD states.

After Table 5:

We investigated statistically significant difference among the ACC of the three-classes classifiers with non-parametric Friedman test. There were a significant difference among ACC of ND_CD_ED, ND_CD_MD and ND_CD_MD recognition systems ($ACC_{ND,CD,ED} = 81.55 \pm 2.6561, ACC_{ND,CD,MD} = 81.94 \pm 2.5203\ and\ ACC_{ND,ED,MD} = 66.42 \pm 1.8937,$ P<0.001). For calculating the significant difference between two of them, we used non-parametric Posthoc Nemenyi test. The ACC of ND-CD-ED and ND-CD-MD recognition systems was significantly different (P=0.002). The ACC of ND-CD-ED and ND-ED-MD recognition systems was significantly different (P<0.001). Also, there was significant difference between ACC of ND-CD-MD and ND-ED-MD recognition systems (P<0.001). The results show that emotional and sensory-motor distraction states have the most confusion and separated with the lowest performance. Sensory-motor and cognitive distractions were separated with the highest ACC percentage.

After Fig. 10:

As a result, in Fig. 10 a, b shown, the proposed recognition system had low performance to recognize CD distractor and the same pattern was observed for MD distractor recognition in Fig. 10 c.

After Table 7:

In this section we could recognize types of distractions in three-class (P<0.001) and four-class (P<0.001) states with an accuracy significantly more than chance level.

After Fig. 11:

Fig. 11 visualizes and summarizes the performance of the recognition system. The results show that emotional distraction have been detected with highest ACC among other distraction. The main reason of not achieving perfect classifier performance (Table 7) is distractions confusion.

After Fig. 12:

Fig. 12 shows that ACC of the distraction detection system was the most for detection by SVM classification. We used Wilcoxon sign rank as a non-parametric test between ACC of SVM classification model and ACC of KNN, Bayesian classification models. There was significant difference between ACC of SVM classification model and ACC of KNN classification model (P<0.001). There was significant difference between ACC of SVM classification model and ACC of Bayesian classification model (P<0.001).

After Table 8:

The ACC obtained in this study (99.16%) was the average ACC of 58 subjects obtained by the LOSO validation method. We investigated statistically significant difference between this result and the last study that consider three types of distractions as distracted class vs. normal state. We used one-sample Wilcoxon sign rank test between 58 ACC of detection distracted by SVM and 78.36% ACC of Panagopoulos's study. There was a significant difference between the ACC of this study and the latest study (P<0.001).

In this study, we used the leave-one-subject-out (LOSO) cross-validation. We trained our machine-learning model n times where n is the number of subjects. Each time, the whole data of one person is excluded from training data set and is considered as a test data set. In this way the model is subject-independent and is more generalizable than k-fold cross-validation.

In Section 2.7 we added this sentence:

In this way the model is subject independent and is more generalizable than k-fold cross validation.

Zahra Bahmani

https://orcid.org/0000-0003-2433-9749

Employment (1)

Tarbiat Modares University: Tehran, Tehran, IR
2019-09-22 to present | assistant professor (Faculty of Elec trical & Computer Engineering)
Employment
Source: Zahra Bahmani

Education and qualifications (3)

Institute for Research in Fundamental Sciences: Tehran, Tehran, IR
2012-09-22 to 2018-09-22 | PhD (Cognitive science)
Education
Source: Zahra Bahmani

Amirkabir University of Technology: Tehran, Tehran, IR
2008-09-22 to 2011-06-22 | Msc (Faculty of Computer Engin eering)
Education
Source: Zahra Bahmani

Amirkabir University of Technology: Tehran, Tehran, IR
2004-09-22 to 2008-09-21 | Bsc (Faculty of Computer Engin eering)
Education
Source: Zahra Bahmani

Works (6 of 6)

Differential Contributions of Inhibitory Subnetwork to Visual Cortical Modulations Identified via Computational Model of Working Memory

Frontiers in Computational Neuroscience

2021-05-20 | journal-article

DOI: 10.3389/fncom.2021.632730

Part of ISSN: 1662-5188

Source: Zahra Bahmani

Effect of perceived interpersonal closeness on the joint Simon effect in adolescents and adults.

Scientific reports

2020-10 | journal-article

PMID: 33093544

PMC: PMC7582195

DOI: 10.1038/s41598-020-74859-3

Source: Zahra Bahmani *via* Europe PubMed Central

Frontotemporal Coordination Predicts Working Memory Performance and its Local Neural Signatures

2020-03 | preprint

OTHER-ID: PPR116050

DOI: 10.1101/2020.03.05.976928

Source: Zahra Bahmani *via* Europe PubMed Central

Prefrontal Contributions to Attention and Working Memory.

Current topics in behavioral neurosciences

2019-01 | journal-article

PMID: 30739308

PMC: PMC6689265

DOI: 10.1007/7854_2018_74

Source: Zahra Bahmani *via* Europe PubMed Central

Working Memory Enhances Cortical Representations via Spatially Specific Coordination of Spike Times.
Neuron
2018-02 | journal-article
PMID: 29398360
PMC: PMC5823767
DOI: 10.1016/j.neuron.2018.01.012
Source: Zahra Bahmani*via*Europe PubMed Central

Brain activity preceded awareness in Libet's experiment is probably related to unconscious inhibition.
The Journal of neuropsychiatry and clinical neurosciences
2013-01 | journal-article
PMID: 23487224
DOI: 10.1176/appi.neuropsych.12020045
Source: Zahra Bahmani*via*Europe PubMed Central

Record last modified Jul 13, 2022, 10:03:11 AM

Research Highlights

- Functional connectivity features increased accuracy of the distraction detection.
- Relation of breathing rate and thermal images of perinasal was the most effective.
- Types of distractions including sensory-motor, cognitive & emotional were recognized.
- Different cognitive distractions distinctly modulated connectivity between signals.

Distracted driving recognition based on functional connectivity analysis between physiological signals and perinasal perspiration index

Nilufar Vosugh[a], Zahra Bahmani*[b], Amin Mohammadian [c]

[a] Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, V.nilufar@modares.ac.ir.

[b] Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, z.bahmani@modares.ac.ir.

[c] Research Center for Development of Advanced Technologies, Post Code:1114112312, mohammadian@rcdat.ir, Tehran, Iran.

** Corresponding author.*

Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, *Email address:* *z.bahmani@modares.ac.ir, phone number: 00989127252354.*

Distracted driving recognition based on functional connectivity analysis between physiological signals and perinasal perspiration index

Nilufar Vosugh[a], Zahra Bahmani*[b], Amin Mohammadian[c]

[a] Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, V.nilufar@modares.ac.ir.

[b] Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, z.bahmani@modares.ac.ir.

[c] Research Center for Development of Advanced Technologies, Post Code:1114112312, mohammadian@rcdat.ir, Tehran, Iran.

** Corresponding author.*

Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, *Email address:* *z.bahmani@modares.ac.ir, phone number: 00989127252354.*

ABSTRACT

Automatic detection of distracted driving is essential to ensure safety of drivers. In this paper, a novel set of features were extracted from thermal and physiological signals in order to detect and recognize distraction of drivers. Thermal video data which measured the temperature of different areas of the face, heart rate, breathing rate and behavioural signals were used while various types of distractions including cognitive, emotional and sensory-motor were applied to the subjects. The proposed discriminator features were extracted by different functional connectivity methods between the perinasal perspiration extracted from thermal images of the face and physiological variables of heart rate and breathing rate. After feature extraction, binary classification methods were applied to detect the distractions. The results showed that using functional connectivity features significantly increases the accuracy of distraction detection system (99.16%). Hence, the proposed model significantly improved (P<0.001) the detection of distraction compared to previous studies. Furthermore, we used the same feature set to recognize different types of distractions by using three-class classifiers. The suggested methods distinguished three types of distractions with the best accuracy of 81.94% related to cognitive, sensory-motor distraction and no-distraction states. We also tried to discriminate two types of cognitive distractions, analytic and mathematical distractions. The recognition system classified two types of cognitive distractions with an accuracy of 91.78%. The results suggest that there is important and complementary information in the connectivity between facial temperature signals and physiological variables for distraction detection and recognition.

Keywords: Functional connectivity, driving distractions, physiological signals, facial thermal images.

1. Introduction

Distracted driving is a condition that the driver's attention is diverted to other tasks over a period of time. Using a mobile phone or immersing in thoughts and memories can lead to distraction. This disrupted driving involves a lot of financial and personal risks. According to the World Health Organization, in 2016, more than one million drivers lost their lives in accidents (Rana, 2021). As a result, paying attention to the distraction and trying to improve driver assistance systems are important and necessary, especially in today's world where science and technology are growing rapidly. If driver distraction is detected automatically, systems can alert the driver to return his/her focus to the road. This warning will reduce the consequences of driving distraction (Pavlidis, 2018). In general, distraction factors can be divided into three categories: cognitive, emotional and sensory-motor (Fatmi, 2019). Several studies have considered detection of driver distraction. Some of these studies have been performed in real-condition environments, in which the desired signals in the car environment were extracted under different conditions while driving (Osman, 2019; Zhao, 2020; Jain, 2021; Day, 2021; Alzubi, 2022; Huang, 2020). In most of these studies, only physical distraction factors (send SMS, call, drink, make up, …) were used and the best accuracy was 96.74%, published in 2020 (Huang, 2020). Driving simulators make it possible to monitor driving performance in a controlled and safe environment. So, many studies have been tried to understand the distracted driving mechanism using driving simulators (Taamneh, 2017; Tran, 2018; Zhang, 2021; Tango, 2013; Ma, 2022). The behavioral signals can be used for distraction detection (Ma, 2022). Besides, Physiological signals, visible and non-visible videos and brain signals included indicator indexes of distraction (Li, 2021; Fan, 2021; Liang, 2022, Day, 2021). Kian Hamedani et al. proposed a method for non-contact measurement of heart rate using thermal imaging (Hamedani, 2016). Pavlidis et al. recorded and shared a rich dataset of different kinds of signals during driving while different types of distractions including cognitive (CD), emotional (ED) and sensory-motor (MD) distractions were applied to drivers (Pavlidis, 2016). This dataset was called simulator study 1 that included a large number of subjects (Taamneh, 2017). In addition, the dataset considered all aspects that may cause driver distraction, and it is more comprehensive in terms of the number of subjects, age and gender in comparison with other studies (Tran, 2018; Zhang, 2021; Tango et al., 2013).

Using the mentioned dataset, several research works have been done with the two general purposes of statistical modeling of distraction (Pavlidis, 2016; Pavlidis, 2018; Gomez, 2018) and distraction detection systems (Panagopoulos, 2019; Tango et al., 2013; McDonald, 2020; Koohestani, 2019) which is also the purpose of this study. Panagopoulos and Pavlidis used a new algorithm called maximum gradient boosting. They extracted features from three variables including Breathing Rate (BR), Heart Rate (HR), and the Perinasal Perspiration (PP) signals extracted from thermal images and achieved 78.36% accuracy of distraction detection (Panagopoulos, 2019). In addition, Pavlidis et al. presented important results in the short-term prediction of dangerous driving behaviors. In another study detection of sensory-motor distraction of the driver was done by help of vehicle dynamics data with 96% performance (Tango et al., 2013).

McDonald et al. analyzed the physiological and behavioral datasets of drivers with 21 machine learning algorithms, which provided the highest accuracy (65%) using random forest method (McDonald, 2020). Koohestani et al. focused on analyzing driver performance with various machine learning techniques, they measured 97.50% accuracy of sensory-motor distraction detection (Koohestani, 2019).

As mentioned, distraction detection systems should be improved in terms of system's performance and consideration of different distraction factors. Mostly, studies in the field focused on, physical distraction factors (Wang, 2022), however, mental (emotional and cognitive) distraction factors are as dangerous as physical distractions (sensory-motor). Thus, introducing general distraction systems with high performances is necessary. Among recent studies on Pavlidis simulator dataset (Panagopoulos, 2019), the best accuracy was 78.36% for detecting distraction including all factors. Besides, distraction recognition system should be considered as a new module in these systems. Using distraction recognition systems, the types of distraction factors are also predicted. Distraction factors can be handled differently in real applications for drivers.

In general, the main purpose of this study is to improve the performance of the distraction detection system. A distraction recognition system is proposed which can discriminate all three types of distraction factors (mental and physical). We focused on the connectivity between physiological and thermal variables of the driver signals as a new informative approach. In Section 2, materials and methods are described in detail. The results are presented in Section 3 followed by conclusion in Section 4.

2. Material and methods

2.1. Task

Simulator study 1 dataset was obtained by Pavlidis group. We will briefly explain about the task and data. For complete details of the task and dataset, refer to Taamneh et al., 2017 and Pavlidis et al., 2016.

Using simulator driving, subjects drove several different sessions. The sessions were practice drive (PD), relaxing drive (RD), No-distracted drive (ND), cognitive distraction driving (CD), emotional distraction driving (ED) and sensory-motor distraction driving (MD). PD is designed to learn the environment of the simulator. In RD and ND, subjects drove without any distractions. Finally, drivers experienced driving with cognitive, emotional, and sensory-motor distractions. In this experiment each distraction session contained 5 phases. The defined distraction factor is only applied in phases 2 and 4 of each session. During phases 1, 3 and 5 no distraction was applied to the subjects. In our study, to detect distraction more closely, phases 2 to 4 in which the distraction factors were applied to the drivers were considered as distracted phases. The CD sessions had two different types of cognitive distraction factors that are called analysis and mathematical questions (CD_AQ, CD_MQ) applied in different phases (2 and 4). Here, only phases that the cognitive distraction factors were applied directly to the drivers were considered as distracted phases (phases 2 and 4). See references Taamneh et al., 2017 and Pavlidis et al., 2016 for further details of tasks and the dataset.

2.2. The general process of this study

To improve the performance of the distraction detection system, in this study we propose features based on connectivity analysis between physiological and thermal variables of driver signals. Fig. 1 shows the block diagram of the proposed method. First, desired driver signals were selected from Simulator Study 1 dataset. These variables were normalized using z-score formula 1. Then, the signals were segmented, classic and connectivity features were extracted from the signals. These features were used for training classification models and finally performance of the system was examined to detect driving distraction.

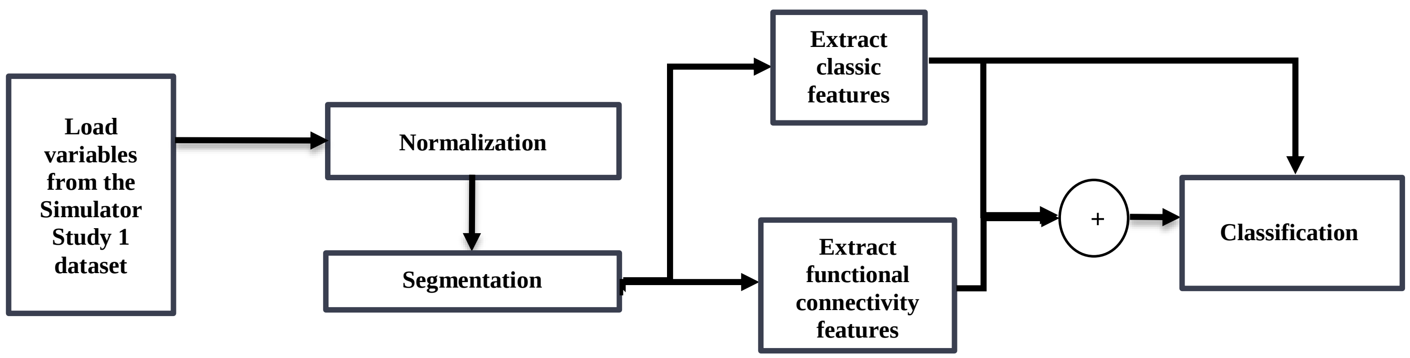


Fig. 1. Block diagram of the proposed method.

According to Fig. 2, some of the physiological and behavioral variables of drivers have been measured in the Simulator Study 1 dataset (Taamneh, 2017). We examined four signals including BR and HR as typical physiological variables of drivers, PP that is extracted from thermal images as thermal physiological and the Lane Offset (LO) as a behavioral variable. Contrary to physiological signals that were obtained from wearable sensors, PP is an arousal index of perinasal perspiration estimated by non-contact thermal camera.

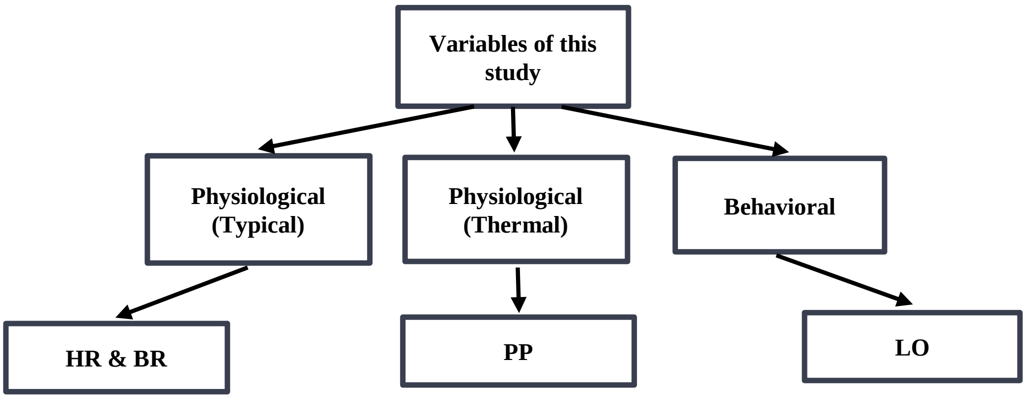


Fig. 2. Four variables from the three categories of signals used in this study. HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset.

According to the Simulator Study 1 dataset (Taamneh, 2017), it was not possible to extract PP of all subjects due to having facial hair in the area around the nose. Also, the BR signal of subject number 67 was not defined due to experimental problems. Therefore, we had signals of 58 subjects in this study.

2.3. Normalization

As preprocessing, we used a within subject normalization method called Z-Score (Equation 1). In this method, we subtracted each sample (*i*) of signal (*x*) from the average of samples (μ) and divided it by standard deviation (*S*). This process was applied on each signal for each subject separately.

$$Z_{Score} = (x_i - \mu)/ S \quad (1)$$

2.4. Segmentation

In accordance with (Panagopoulos, 2019), the signals were segmented in windows of size 10 with 90% overlap between successive windows.

2.5. Feature extraction

We examined two types of feature sets, one of them was the classic feature set and the other one uses the features based on the connectivity of two signals. Both categories of features were defined in the time domain. We used connectivity features among physiological, thermal and behavioral signals in order to detect and recognize distraction for the first time in this field. These types of features have not been used in the previous studies. The purpose of defining classic features was to investigate the effect of connectivity features in improvement of the system performance. We divided the classic features into statistical and structural categories. Table 1 shows the types of these features. These statistical and structural features were extracted from 10 seconds time windows of the signals. As a result, 11 classic features were extracted from each time window of signals. Using 4 signals, we obtained 44 features from each time window of the classic feature set.

Table 1. Types of classic features: statistical and structural.

Statistical	Structural
Variance	**Maximum**
Median	**Minimum**
Standard deviation	**Maximum -Minimum**
Mode	**Skewness**
Mean	**Kurtosis**
Entropy	-

In the functional connectivity features, the connectivity between two signals was investigated. Since the non-contact signal (PP) was reported as an effective signal in detecting driver distraction (Panagopoulos, 2019Tango, 2013), PP has always been considered as one of the pairs for measuring connectivity. In general, 6 non-directional connectivity can be defined among these four signals. We performed our calculations from only 3 connections containing PP, shown in Fig. 3.

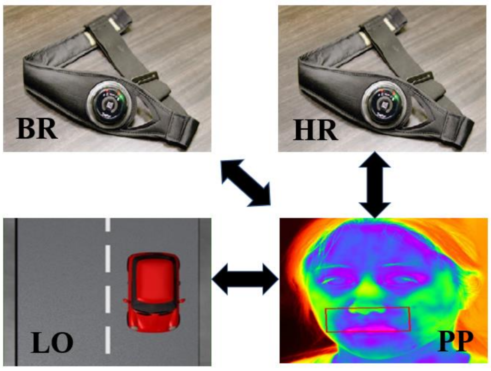


Fig. 3. Three non-directional functional connectivity containing PP were used (PP-BR), (PP-HR) and (PP-LO). HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset. (color should be used for this figure in print)

Functional connectivity which expresses the connectivity between two variables can be measured by different methods. Fig. 4 shows the methods of functional connectivity measurement used in this study.

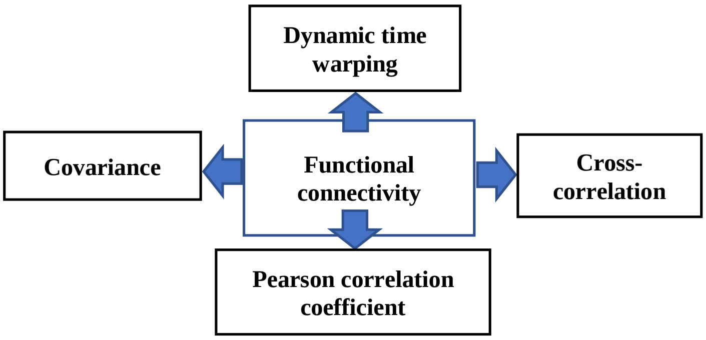


Fig. 4. Different methods of functional connectivity measurement used in this study.

Covariance and correlation can be mentioned as criteria for calculating the functional connectivity between two variables.

$$cov(x,y) = 1/(n-1)\sum_{i=1}^{n}(x_i - \mu_x)(y_i - \mu_y) \qquad (2)$$

Equation 2 shows how the covariance (*cov*) of the two signals *x, y* is calculated from observations of each signal and the mean of the signals (μ_x, μ_y); n is the sample size and *i* is the index of each sample of signals. It shows what happens to *y* with changes in *x*, and vice versa. The correlation is a normalized covariance with values between 1 and -1. The correlation between the two signals were calculated as the correlation coefficient (Equation 3).

$$\rho_{xy} = cov(x,y)/\sqrt{\sigma_x^2 * \sigma_y^2} \qquad (3)$$

In this equation *cov(x,y)* is the covariance between two signals *x,y* and σ_x^2, σ_y^2 are the variances of the two signals *x,y*, respectively. The correlation coefficient (ρ) between two variables (*x, y*) indicates the ability to predict the value of one variable from the other. Depending on the type of data, there are different ways to measure the correlation coefficient. In general, three types of correlation coefficients are defined: 1. Pearson 2. Spearman and 3. Kendall correlation coefficient. One of the most usual ways to measure the dependence between two quantitative variables is to calculate the Pearson correlation coefficient. Using the Cauchy-Schwartz inequality, it can also be shown that the absolute value of the correlation coefficient will never be greater than one.

Cross-correlation between two signals was examined as another type of functional connectivity that deals with the similarity of two signals (Yoo, 2009). Here, Cross-correlation was used to calculate the connectivity features, which is the product of the internal multiplication of two signals. The Cross-correlation of two signals of length 10*1 has 19 samples, and because we defined one feature for each time window, we used the maximum, minimum and mean values of these 19 samples as functional connectivity features.

Dynamic time warping calculates the statistical distance between two signals. This time domain algorithm extends the two vectors from the window samples of both signals over a set of common moments, so that the sum of the Euclidean distances between the corresponding regions is the smallest value.

Three lines of connectivity were defined between PP and BR, PP and HR, as well as between PP and LO. For each pair of signals, 6 functional connectivity features were extracted using the mentioned methods. Totally, we had 18 connectivity features from each time window of signals. Next, we examined the driver distraction detection by machine learning methods using these 62 features (44 classic and 18 connectivity features). we had 161755 samples of all windows for distracted detection and normal classes.

The extracted features were monitored and the non-informative features were excluded. The criteria of excluding features were: 1. The variance of the features was less than 0.001. 2. The sum of the samples of those features was zero. 3. Existence of very large values in the feature vectors. All feature vectors were normalized to mean 'zero' and variance 'one'.

2.6. Classification

We designed a binary classifier for the distraction detection system and several multi-class classifiers for the recognition systems. In the detection system, two-class mode of driver distraction was considered (distracted driving vs. normal driving). In the recognition systems, three-class modes (CD, ED, ND; CD, MD, ND; ED, MD, ND) and four-class mode were focused (CD, ED, MD and ND). In the Following, the detailed description of detection and categorization systems is explained.

Distraction detection system: First, we combined all three types of CD, ED and MD sessions into a class called distracted class and considered the ND, RD and PD sessions as the normal class. In the next step, we classified distracted and normal classes. We used Naive Bayes as the basic classification method for distraction detection. Bayesian classifier was used as a machine learning method to model the distraction detection system. Bayesian classifier has an acceptable speed and accuracy for this huge dataset (Taamneh, 2017). Besides, the systems were modeled with Support Vector Machines (SVM) and K-Nearest Neighborhood (KNN) methods. In previous studies, mostly one distraction factor has been considered as distracted driving class. Here, we also designed binary classifiers for detecting each distracted driving from no-distracted drive (ND vs. CD, ND vs. ED, ND vs. MD). The purpose was to know how we can detect each factor of distraction from ND and to be able to justify the superiority of the proposed method over other methods and studies. It should be noted that only in the first case of binary class (considering all combined distraction factors as distracted driving class), three sessions of ND, RD and PD were considered as the normal one. In other cases, in order to keep balance of sample sizes among classes, only ND session was considered as the normal class.

The inputs of classifiers in the detection system were features extracted from all pairs of signals (BR-PP, HR-PP, LO-PP). Also, in order to separately analyze the effect of each distraction factor on each signal, distraction detection systems were trained using features extracted from only one pair of signals.

Distraction recognition system (three-class mode): The purpose of this section was to investigate the separability of different distracted factors with each other (in the absence of the third factor). We trained different three-class systems in order to recognize the types of distraction factors besides detecting distraction. Cognitive distractions, which are considered as mental factors, were applied to the driver using two different stimuli. Firstly, analytical questions were asked by the experimenter, which required logical comparison, secondly, mathematical questions were asked from the driver and the subject had to do mental calculations. We studied this cognitive distraction factors in more detail. For this purpose, we designed a three-class cognitive recognition system (CD-AQ, CD-MQ, ND). We used Bayesian classifier in this mode.

Distraction recognition system (four-class mode): One of the innovations of this study compared to previous studies is investigating the discriminability of distraction factors using physiological, thermal and behavioural signals of drivers. Here, we trained a four-class classifier for recognition of the types of distractions (CD, ED, MD and ND). Bayesian classifier was used in this mode.

2.7. Leave One Subject Out cross validation (LOSO)

To evaluate how the machine learning model is generalized to a new subject, we used LOSO cross validation. In this method, we excluded the whole data of one subject from training dataset and considered the data of that subject as test dataset. Then, we trained the model with the training data set and then tested it with the test dataset. In this way the model is subject-independent and is more generalizable than k-fold cross-validation. This process was repeated 58 times (number of subjects), and the final performance was reported as the average performance of all subjects.

3. Results

In this section, the results are presented and analyzed. We modeled the distraction systems using two sets of classic and functional connectivity features. Among all the classic features extracted from driver signals, four categories of features were included according the exclusion criteria (The last paragraph of section 2.5). These features are mentioned in Table 2.

Table 2. Included sets of classic features which were used in this study. HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset.

All statistical features of BR, PP
All structural features of PP
Entropy of HR, LO
Max, min, max-min of BR

As shown in Table 2, all classical (statistical and structural) features of the PP signal passed the filter criteria and were considered as features for classification training.

3.1. Distraction detection system:

3.1.1. The impact of functional connectivity features on distraction detection system

We used different criteria to evaluate the classification algorithms. Accuracy (ACC) is the first and simplest criterion, which is equal to the number of cases we predicted correctly divided by the total number of observations. ACC is the main criterion of this research which has been mentioned in previous studies. In this study, all reported values of ACC are accuracy of the test dataset that were averaged from all epochs. F1 (Fisher-measure) is a type of average system ACC between the predicted data and the recall. The reason for choosing this criterion was the unequal number of samples in each class in some cases. Other criterion is Area Under the Curve (AUC) of Receiver Operating Characteristics (ROC). ROC is a graphical chart that shows the detection ability of a binary classification system. The larger the AUC, the more ideal.

In this part we used 44 classic features of all variables (BR, HR, LO, PP) and trained a Bayesian classifier as distraction detection model. As shown in Table 3, the ACC of detection between distracted and normal driving was 59.40% ($ACC_{distracted\ vs.\ normal} = 59.40\%, AUC_{distracted\ vs.\ normal} = 0.64, F1_{distracted\ vs.\ normal} = 0.28$). After adding 18 functional connectivity features, the ACC of distraction detection reached 96.31% ($ACC_{distracted\ vs.\ normal} = 96.31\%, AUC_{distracted\ vs.\ normal} = 1, F1_{distracted\ vs.\ normal} = 0.96$).

Table 3. Performance of Bayesian classification to detect driver distraction from normal case by using classic features and functional connectivity features.

Features	ACC (%)	AUC	F1
Classic	59.40	0.64	0.28
Classic + connectivity	96.31	1	0.96

In this case, more that 30% increase in ACC was obtained by using connectivity features. We used Wilcoxon signed rank test for investigating statistically significant differences of performance measurements between classic and total feature sets of Table 3. There was statistically significant difference between ACC of classic features and ACC of classic and connectivity (total) features (P<0.001). There was statistically significant difference between AUC of classic and total features (P<0.001), and there was statistically significant difference between F1 of classic features and F1 of total features (P<0.001). This analysis shows that, the performance of the distraction detection system after adding connectivity features was significantly enhanced. These results indicate that new and complementary information exists in the connectivity between physiological, thermal and behavioral signals. Fig. 5 demonstrates the bar plot of the ACC of the detection system for each subject using classic features (red lines) and both classic and functional connectivity features (blue lines). In this figure, the ACC of each subject is plotted (note that no information of this subject was observed by trained model). As mentioned in section 2.7 the validation method is LOSO, the final ACC was calculated by averaging ACC of each test subject.

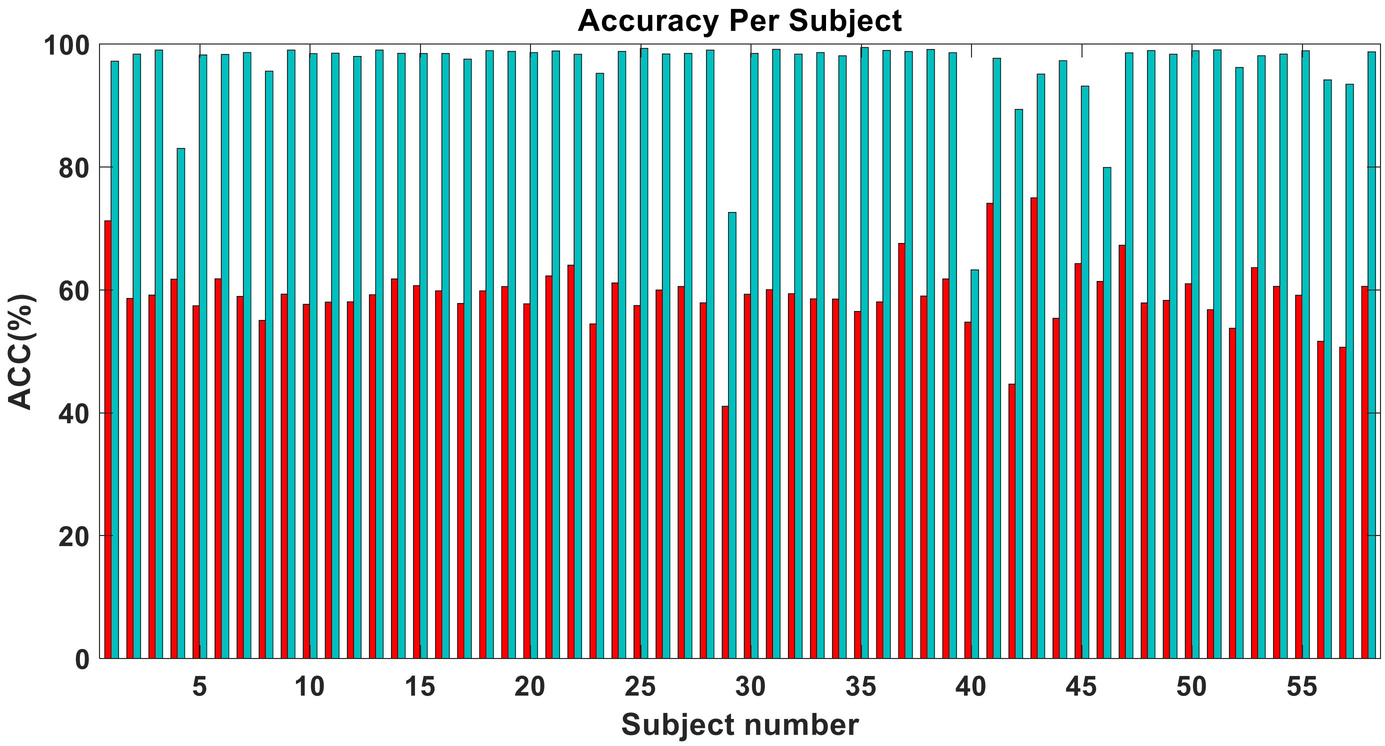
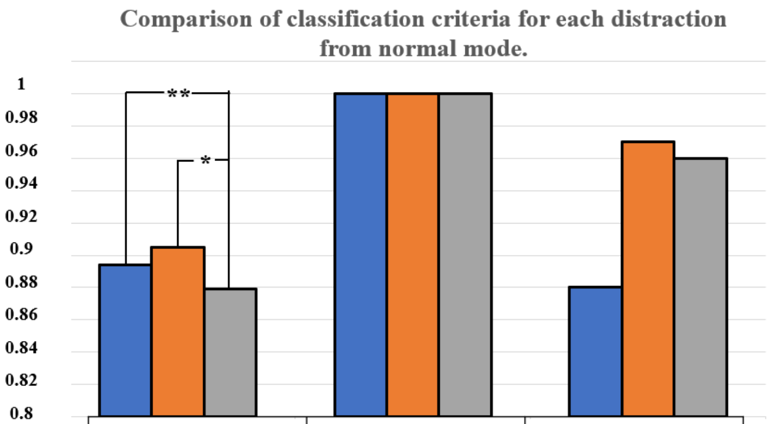


Fig. 5. Bar plot of the accuracy (ACC) of each subject in distraction detection system: classification ACC, using classic features (red), adding connectivity features (blue). (color should be used for this figure in print)

Fig. 5 shows the effectiveness of the functional connectivity features for each subject. All 58 subjects showed noticeable improvement in ACC of distraction detection.

3.1.2. The difference of distraction factors in detection system

In Fig. 6 distraction detection system was evaluated based on each distraction factor separately. Using total features (classic + connectivity), we obtained 89.38% ACC of detection between CD and ND, 90.47% ACC of detection system between ED and CD and 87.89% ACC of detection system between MD and ND ($ACC_{ND\ vs.\ CD} = 89.38\%, AUC_{ND\ vs.\ CD} = 1, F1_{ND\ vs.\ CD} = 0.88, ACC_{ND\ vs.\ ED} = 90.47\%, AUC_{ND\ vs.\ ED} = 1, F1_{ND\ vs.\ ED} = 0.97, ACC_{ND\ vs.\ MD} = 87.89\%, AUC_{ND\ vs.\ MD} = 1, F1_{ND\ vs.\ MD} = 0.96$).



	ACC	AUC	F1
ND-CD	0.8938	0.99	0.88
ND-ED	0.9047	0.99	0.97
ND-MD	0.8789	0.99	0.96

Fig. 6. Results of Bayesian classification to detect each distraction factors (CD=Cognitive Drive, ED=Emotional Drive and MD=sensory-Motor Drive) from ND (No-distracted Drive) using all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

The results showed that the ED with the highest ACC and F1 was the most detectable factor from the no-distraction mode.

We used Wilcoxon sign rank test for investigating significant differences between mental and physical distractions. There was statistically significant difference between ACC of ND_MD as the physical distractor and ND_ED as the mental distraction (P<0.001). Also, there were statistically significant difference between ND_MD as the physical distractor and ND_CD as the mental distraction (P=0.015). As a result, this connectivity feature set could detect mental distraction better than the physical one.

3.1.3. The impact of different signals in detection system

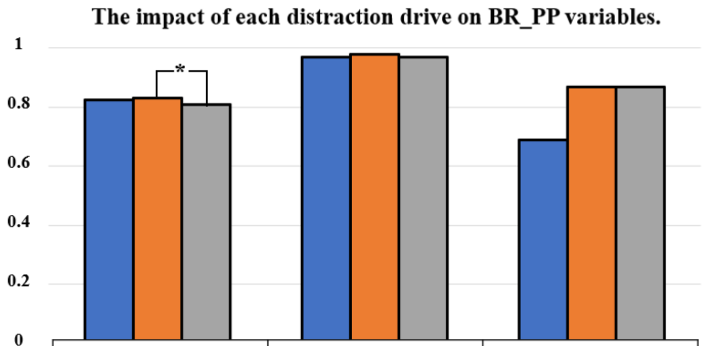
System performance using all three pairs of PP-HR, PP-BR, and PP-LO for feature extraction and classification were examined. The purpose of this analysis, as shown in Table 4, was to distinguish the most useful and informative pair of signals mentioned in the distraction detection system. We obtained 93.72% ACC of detection between distracted vs. ND for just features extracted of BR, PP signals with 6 connectivity and 22 classic features ($\mathrm{ACC}_{\mathrm{BR-PP,\ distracted\ vs.\ ND}} = 93.72\%, AUC_{\mathrm{BR-PP,\ distracted\ vs.\ ND}} = 0.99, F1_{\mathrm{BR-PP,\ distracted\ vs.\ ND}} = 0.92$). 92.13% ACC of detection system between distracted vs. ND for just features extracted of HR, PP signals ($\mathrm{ACC}_{\mathrm{HR-PP,\ distracted\ vs.\ ND}} = 92.13\%,\ AUC_{\mathrm{HR-PP,\ distracted\ vs.\ ND}} = 0.98, F1_{\mathrm{HR-PP,\ distracted\ vs.\ ND}} = 0.91$) and 60.02% ACC of detection system between distracted vs. ND for just features extracted of LO, PP signals were achieved. ($\mathrm{ACC}_{\mathrm{LO-PP,\ distracted\ vs.\ ND}} = 60.02\%, AUC_{\mathrm{LO-PP,\ distracted\ vs.\ ND}} = 0.90, F1_{\mathrm{LO-PP,\ distracted\ vs.\ ND}} = 0.66$).

Table 4. Bayesian classification results of distraction detection using coupling variables. HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset.

connectivity	ACC (%)	AUC	F1
BR-PP	93.72	0.99	0.92
HR-PP	92.13	0.98	0.91
LO-PP	60.02	0.90	0.66

In this case, we used both the classic and the functional connectivity features associated with each pair of variables. We investigated statistically significant differences among the ACC of distraction detection system using BR-PP, HR-PP and LO-PP pairs of signals with non-parametric Friedman test. There was significant difference among ACC of BR_PP, HR_PP and LO_PP ($\mathrm{ACC}_{\mathrm{BR-PP,\ distracted\ vs.\ ND}} = 93.72\% \pm 3.0074,\ \mathrm{ACC}_{\mathrm{HR-PP,\ distracted\ vs.\ ND}} = 92.13 \pm 0.9081,\ \mathrm{ACC}_{\mathrm{LO-PP,\ distracted\ vs.\ ND}} = 60.02 \pm 5.3140 * 10^{-5}$, P<0.001). Using Friedman test, there was significant difference among the AUC of these three groups of signals (P<0.001). Also, there was significant difference among the F1 of these three groups of signals (P<0.001). For calculating the significant difference between two of them, we used non-parametric Posthoc Nemenyi test. The ACC (P<0.001) and F1 (P<0.001) of BR_PP and LO_PP were significantly different and the ACC (P<0.001) and F1 (P<0.001) of HR_PP and LO_PP were also significantly different. But the ACC (P=0.742) and F1(P=0.301) of BR_PP and HR_PP wasn't significantly different. The AUC of BR_PP and LO_PP (P<0.001), HR_PP and LO_PP (P<0.001) was significantly different. Also, the AUC of BR_PP and HR_PP was significantly different (P<0.001). As a result, the connectivity between BR_PP and HR_PP were informative pairs of signals for distraction detection. According to the results of Table 4, BR_PP seems to contain more information than all other pairs of signals. In all three performance measurements, BR_PP performed significantly better than LO_PP. But compared to the HR_PP, only the F1 criterion was significantly higher. However, ACC and AUC using BR_PP was higher than that of HR_PP, the differences were not statistically significant.

Fig. 7 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on BR_PP variables. We obtained 82.58% ACC of detection between CD and ND ($ACC_{ND\ vs.\ CD} = 82.58\%, AUC_{ND\ vs.\ CD} = 0.97\ and\ F1_{ND\ vs.\ CD} = 0.69$), 82.94% ACC of detection between ED and ND ($ACC_{ND\ vs.\ ED} = 82.94\%, AUC_{ND\ vs.\ ED} = 0.98\ and\ F1_{ND\ vs.\ ED} = 0.87$) and 80.97% ACC of detection between MD and ND for just features extracted of BR, PP signals ($ACC_{ND\ vs.\ MD} = 80.97\%, AUC_{ND\ vs.\ MD} = 0.97\ and\ F1_{ND\ vs.\ MD} = 0.87$).

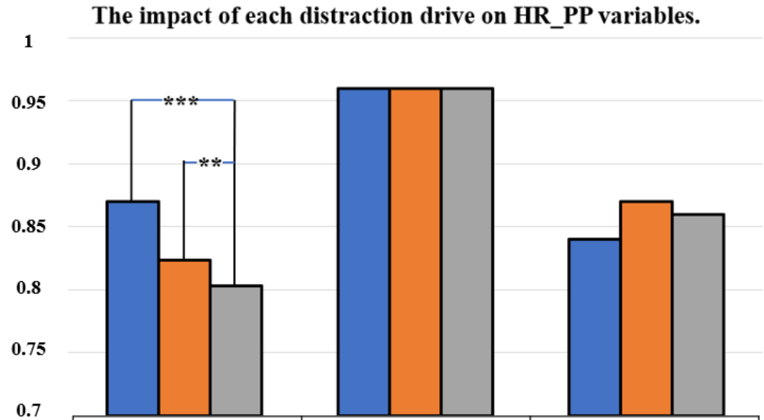


	ACC	AUC	F1
ND-CD	0.8258	0.97	0.69
ND-ED	0.8294	0.98	0.87
ND-MD	0.8097	0.97	0.87

Fig. 7. Results of Bayesian classification for BR_PP as a paired connectivity variables with all classic and connectivity features. BR: Breathing rate, PP: Perinasal perspiration. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

Fig. 7 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for compression. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There wasn't any significant difference between ACC of the system for classifying MD as physical distractor and CD as mental distractor from normal state in this case (P=0.439). There was significant difference between ACC of the system for classifying MD as physical distractor and ED as mental distractor from normal state in this case (P<0.001).

Fig. 8 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on HR_PP variables. We obtained 86.96% ACC of detection between CD and ND ($ACC_{ND\ vs.\ CD} = 86.96\%, AUC_{ND\ vs.\ CD} = 0.96\ and\ F1_{ND\ vs.\ CD} = 0.84$), 82.33% ACC of detection between ED and ND ($ACC_{ND\ vs.\ ED} = 82.33\%, AUC_{ND\ vs.\ ED} = 0.96\ and\ F1_{ND\ vs.\ ED} = 0.87$) and 80.27% ACC of detection between MD and ND for just features extracted of BR, PP signals ($ACC_{ND\ vs.\ MD} = 80.27\%, AUC_{ND\ vs.\ MD} = 0.96\ and\ F1_{ND\ vs.\ MD} = 0.86$).



	ACC	AUC	F1
ND-CD	0.8696	0.96	0.84
ND-ED	0.8233	0.96	0.87
ND-MD	0.8027	0.96	0.86

Fig. 8. Results of Bayesian classification for HR_PP as a pair of connectivity variable with all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***) HR: Heart rate, PP: Perinasal perspiration. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive (color should be used for this figure in print)

Fig. 8 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for comparison. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There was significant difference between system performances for classifying ED as mental and MD as physical distractions from normal state in this case (P<0.01). There was significant difference between system performances for classifying CD as mental and MD as physical distractions from normal state in this case (P<0.05).

Fig. 9 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on LO_PP variables. We obtained 85.23% ACC of detection between CD and ND ($ACC_{ND\ vs.\ CD} = 85.23\%, AUC_{ND\ vs.\ CD} = 0.96\ and\ F1_{ND\ vs.\ CD} = 0.84$), 84.89% ACC of detection between ED and ND ($ACC_{ND\ vs.\ ED} = 84.89\%, AUC_{ND\ vs.\ ED} = 0.98\ and\ F1_{ND\ vs.\ ED} = 0.91$) and 81.83% ACC of detection between MD and ND for just features extracted of BR, PP signals ($ACC_{ND\ vs.\ MD} = 81.83\%, AUC_{ND\ vs.\ MD} = 0.98\ and\ F1_{ND\ vs.\ MD} = 0.88$).

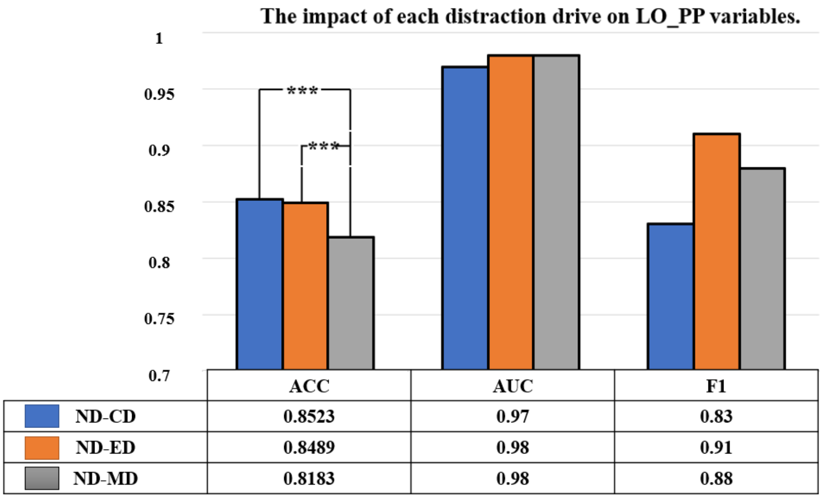


Fig. 9. Results of Bayesian classification for LO_PP as a pair of connectivity variable with all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). PP: Perinasal perspiration and LO: Lane offset. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive (color should be used for this figure in print).

Fig. 9 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for comparison. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There was significant difference between system performances for classifying ED as mental and MD as physical distractions from normal state in this case (P<0.05). There was significant difference between system performances for classifying CD as mental and MD as physical distractions from normal state in this case (P<0.05).

As a result of Fig. 7, Fig. 8 and Fig. 9 ACC of the distraction detection system was the most for discrimination between ND and CD states. For HR-PP and LO-PP variables, the ACC of the physical (MD) and mental (ED and CD) distraction detection system was significantly different. The results show that emotional and cognitive factors have the greatest impact on modulating all three pairs of variables. Thus, connectivity features are effective in identifying the causes of mental distraction. Obviously, physical distraction mostly modulates behavioral variables such as steering angle and gaze position which are not considered in this study as we focused on detecting distraction from physiological states of body and brain.

3.2. Distraction recognition system (three-class):

3.2.1. Separability of different distraction factors

The purpose of this section is to test the discriminability of different kinds of distraction states. We performed the three-class classification in order to investigate how different distraction factors modulate physiological signals of drivers. As shown in Table 5, All classic and connectivity features were extracted from three pairs of PP-HR, PP-BR, and PP-LO signals. The AAC of 81.55% were obtained for recognition among ND, CD, ED classes ($ACC_{ND,CD,ED} = 81.55\%, F1_{ND,CD,ED} = 0.84$). ND, CD, MD classes were recognized with 81.94% ACC ($ACC_{ND,CD,MD} = 81.94\%, F1_{ND,CD,MD} = 1$) and ND, CD, MD were classified with 66.42% ACC ($, ACC_{ND,ED,MD} = 66.42\%$).

Table 5. Results of three-class distraction recognition system. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive

Classes	ACC (%)	F1
ND, CD. ED	81.55	0.84
ND, CD, MD	81.94	1
ND, ED, MD	66.42	-

We investigated statistically significant difference among the ACC of the three-classes classifiers with non-parametric Friedman test. There were a significant difference among ACC of ND_CD_ED, ND_CD_MD and ND_CD_MD recognition systems ($ACC_{ND,CD,ED} = 81.55 \pm 2.6561, ACC_{ND,CD,MD} = 81.94 \pm 2.5203\ and\ ACC_{ND,ED,MD} = 66.42 \pm 1.8937$, P<0.001). For calculating the significant difference between two of them, we used non-parametric Posthoc Nemenyi test. The ACC of ND-CD-ED and ND-CD-MD recognition systems was significantly different (P=0.002). The ACC of ND-CD-ED and ND-ED-MD recognition systems was significantly different (P<0.001). Also, there was significant difference between ACC of ND-CD-MD and ND-ED-MD recognition systems (P<0.001). Sensory-motor and cognitive distractions were separated with the highest ACC percentage. Fig. 10 shows the confusion matrix of all three states of Table 5.

(94.21%) 35510	**(1.21%)** 458	**(4.57%)** 1723
(2.23%) 353	**(52.85%)** 8367	**(44.91%)** **7109**
(4.23%) 1172	**(2.71%)** 751	**(93.05%)** 25757

(a)

(94.92%) 35780	**(0.89%)** 336	**(4.17%)** 1575
(2.17%) 345	**(53.55%)** 8477	**(44.26%)** 7007
(3.26%) 913	**(4.09%)** 1146	**(92.64%)** 25931

(b)

(96.17%) 36248	**(0.48%)** 183	**(3.34%)** 1260
(2.99%) 830	**(21.11%)** 5844	**(75.88%)** 21006
(3.10%) 869	**(16.85%)** 4718	**(80.03%)** 22403

(c)

Fig. 10. Confusion matrixes of the different three-class recognition system. a) Confusion matrix of recognition system among ND, CD, ED. b) Confusion matrix of recognition system among ND, CD, MD. c) Confusion matrix of recognition system among ND, MD, ED. (color should be used for this figure in print)

As a result, in Fig. 10 a, b shown, the proposed recognition system had low performance to recognize CD distractor and the same pattern was observed for MD distractor recognition in Fig. 10 c.

3.2.2. Discriminability of different types of cognitive distractions

In this section, we study the cognitive factors in more detail. The cognitive distraction factors were applied to subjects by the experimenter using two different categories of analytical and mathematical questions. We want to discriminate these two types of cognitive distraction states and the no-distracted state. For one of the subjects, only the results of the analysis questions were presented in the data set, so this subject is excluded from analysis and the results were measured from 57 drivers. AS shown in Table 6, we obtained 91.78% ACC of recognition among CD_AQ, CD_MQ, ND ($ACC_{ND,CD-AQ,CD-MQ} = 91.78\%, F1_{ND,CD-AQ,CD-MQ} = 0.93$).

Table 6. Results of recognition among two different types of cognitive distraction, mathematical questions (CD_MQ = CD1) and analytical questions (CD_AQ = CD2) and no-distraction (ND).

Classes	ACC (%)	F1
ND, CD1, CD2	91.78	0.93

In mathematical questions, subjects should mentally perform a series of operations of addition and subtraction of multi-digit numbers, while in analytical questions, different logical and analytical questions were answered by drivers.

3.3. Distraction recognition system (four-class)

In this step, we examine the discriminability of four-class states including three types of distraction and no-distraction states. The result of the classifier performance is presented in Table 7. We obtained 63.39% ACC of recognition among ND, CD, ED, MD using all classic and connectivity features ($ACC_{ND\ vs.\ CD\ vs.\ ED\ vs.\ MD} = 63.39\%, F1_{ND\ vs.\ CD\ vs.\ ED\ vs.\ MD} = 0.65$).

Table 7. Results of Bayesian classification to recognize types of distraction (four-classes). CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive

Classes	ACC (%)	F1
ND, CD, ED, MD	63.39	0.65

In this section we could recognize types of distractions in three-class (P<0.001) and four-class (P<0.001) states with an accuracy significantly more than chance level. In Fig. 11, the confusion matrix is demonstrated. It should be noted that this ACC is the average ACC of 58 subjects.

(95.81%) 36113	**(0.66%)** 249	**(1.52%)** 573	**(2%)** 756
(1.83%) 290	**(52.83%)** 8364	**(26.77%)** 4239	**(18.54%)** 2936
(3%) 833	**(2.72%)** 753	**(40.32%)** 11161	**(53.94%)** 14933
(2.68%) 751	**(3.67%)** 1030	**(34.72%)** 9719	**(58.91%)** 16490

Fig. 11. Confusion matrix of the four-class recognition system (ND, CD, MD, ED). (color should be used for this figure in print)

Fig. 11 visualizes and summarizes the performance of the recognition system. The results show that emotional distraction have been detected with highest ACC among other distractions. The main reason of not achieving perfect classifier performance (Table 7) is distraction confusion.

3.4. Comparison of distraction detection system using other classifiers

In this section we tried to compare the performance of the proposed method with previous studies. First of all, the distraction detection system is trained with proposed features using different classifiers. The results of the distraction detection systems using other classifiers including SVM and the 5-nearest neighborhood and Bayesian are demonstrated in Fig. 12. We achieved the ACC of 96.31% for detection between distracted and normal driving with Bayesian classifier $\left(ACC_{distracted\ vs.\ normal,\ Bayesian} = 96.31\%, AUC_{distracted\ vs.\ normal,\ Bayesian} = 1, F1_{distracted\ vs.\ normal,\ Bayesian} = 0.96\right)$. We obtained 97.25% ACC of distraction detection using KNN classifier $(ACC_{distracted\ vs.\ normal,\ KNN} = 97.25\%, AUC_{distracted\ vs.\ normal,\ KNN} = 0.98, F1_{distracted\ vs.\ normal,\ KNN} = 0.97)$ and 99.16% ACC of distraction detection system by SVM classifier $\left(ACC_{distracted\ vs.\ normal,\ SVM} = 99.16\%, AUC_{distracted\ vs.\ normal,\ SVM} = 1, F1_{distracted\ vs.\ normal,\ SVM} = 0.99\right)$.

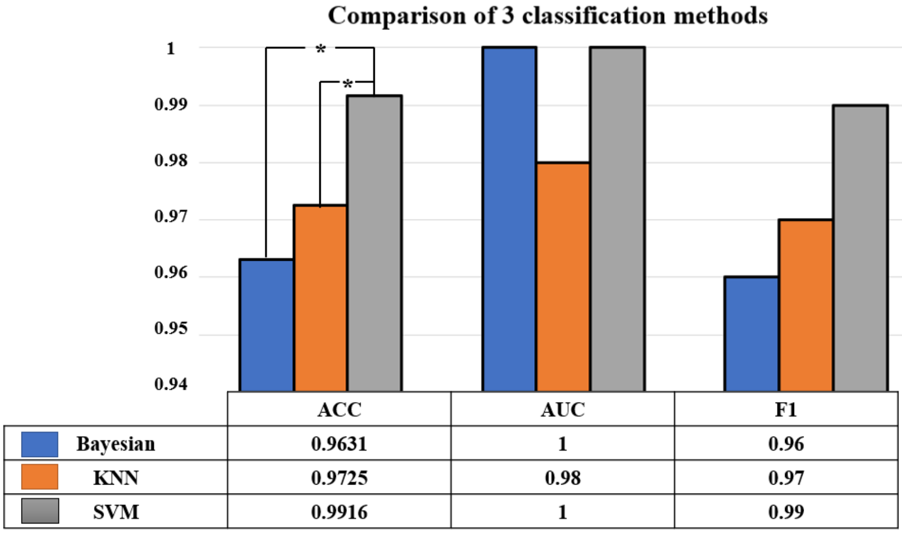


Fig. 12. Comparison of distraction detection system based on Bayesian, KNN and SVM classifiers using all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

Fig. 12 shows that ACC of the distraction detection system was the most for detection by SVM classification. We used Wilcoxon sign rank as a non-parametric test between ACC of SVM classification model and ACC of KNN, Bayesian classification models. There was significant difference between ACC of SVM classification model and ACC of KNN classification model (P<0.001). There was significant difference between ACC of SVM classification model and ACC of Bayesian classification model (P<0.001). The results show that the highest performance of the system is related to the SVM classification with ACC of 99.16%. This study shows the importance of functional connectivity features between physiological signals and PP which significantly improved the ACC of the distraction detection system. A comparison with other studies using this data set is presented in Table 8.

Table 8. Comparison of driver distraction detection in previous studies with the proposed method. Factor 1: Physiological, 2: Behavioral and 3: Thermal signals. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive

Distracted factor	Method	ACC (%)	Input variables	Number of subjects	Reference
MD	Random forest	AUC=91	1+ 3	58	Koohestani et al., 2018
MD	GWO Algorithm	97.50	1 + 3	58	Koohestani et al., 2019
CD, MD	Random forest	65	1 + 2	48	McDonald et al., 2020
CD, ED, MD	XGB Algorithm	78.36	1 + 2 + 3	59	Panagopoulos et al., 2019
CD, ED, MD	**SVM**	**99.16**	**1 + 2 + 3**	**58**	**This study**

As shown in Table 8, in References (Koohestani et al., 2018) and (Koohestani et al., 2019), where the system is relatively well functioning, only the sensory-motor factor (sending SMS) was considered as distracted state. In the study (McDonald et al., 2020), which considered two sensory-motor and cognitive factors as distracted state, the system did not have a high ACC. Only in the article Panagopoulos et al. all three types of sensory-motor, cognitive and emotional distractions were used and the relatively low ACC was achieved. In this study, the LOSO cross validation was used to evaluate the system performance. This generalizable method does not include any kind of information from test subject in training data set. So, the system is designed independent from subjects. The performance of the proposed method outperformed the previous studies while they (Panagopoulos et al., 2019) did not evaluate the system using subject independent classifiers. It should be noted that in most studies, complex algorithms have been used to classify the distraction state, while we used simple classifiers in machine learning. The main reason of increasing performance of the proposed distraction detection system is applying useful and informative features especially functional connectivity between physiological and thermal signals. we used these connectivity features for the first time, which led to higher ACC of distraction detection. We achieved a higher level of ACC to detect the driver's distraction from the normal state than recent studies. The ACC obtained in this study (99.16%) was the average ACC of 58 subjects obtained by the LOSO validation method. We investigated statistically significant difference between this result and the last study that considers three types of distractions as distracted class vs. normal state. We used one-sample Wilcoxon sign rank test between 58 ACC of detection distracted by SVM and 78.36% ACC of Panagopoulos's study. There was a significant difference between the ACC of this study and the latest study ($P<0.001$).

The present study is comprehensive in terms of subject numbers and types of distraction factors. We also used three different types of signals: physiological (BR, HR), behavioral (LO), and thermal (PP) to detect driver distraction. Our innovation, beside the proposed connectivity features, was introduction of distraction recognition systems. For the first time, we could discriminate the types of distractions with acceptable performances. This recognition can enhance the ability of automatic systems in driver industry in order to detect the state of drivers and make preferred suggestions.

4. Conclusion and discussion

In this study we analyzed connectivity as a statistical measure of relationship between signals captured during driver's physiological and behavioral activities in order to extract features for distraction detection. For this evaluation, we modeled the distraction detection systems using two sets of classic (statistical and structural) and functional connectivity features. The ACC of detection between distracted and normal driving using classic features was 59.40%. After adding 18 functional connectivity features, the ACC of distraction detection reached 96.31%. There was statistically significant difference between ACC of classic features and ACC of total features ($P<0.001$). The analysis of the connectivity between the signals indicates a kind of coordinated and non-coordinated tone, which is an appropriate characteristic of changing drivers' mental states due to the presence of distractions. Then, the proposed distraction detection system was evaluated based on each distraction factor separately. As a result, in Fig. 6, the proposed connectivity feature set could detect mental distraction better than physical distraction. Also, we examined the proposed system performance using each pair of PP-HR, PP-BR, and PP-LO for feature extraction and classification. According to the results of Table 4, BR_PP seems to contain more information than all other pairs of signals. As a result of Figs. 7-9, ACC of the distraction detection system took the highest value for discrimination between

ND and CD states. For HR-PP and LO-PP variables, the ACC of the physical (MD) and mental (ED and CD) distraction detection systems was significantly different. The results show that emotional and cognitive factors have the greatest impact on modulating all three pairs of variables. Thus, connectivity features are effective in identifying the causes of mental distraction. Obviously, physical distraction mostly modulates behavioral variables such as steering angle and gaze position which are not considered in this study, as we focused on detecting distraction from physiological states of body and brain. We also performed the three-class classification in order to investigate how different distraction factors modulate physiological signals of drivers. As shown in Table 5, sensory-motor and cognitive distractions were separated with the highest ACC percentage. As a confusion result, presented in Fig. 10 a, b, the proposed recognition system had low performance to recognize CD distractor and the same pattern was observed for MD distractor recognition in Fig. 10 c.

The results in Fig. 12 show that the highest performance of the system is related to the SVM classification with ACC of 99.16%. As shown in Table 8, in references (Koohestani, 2018) and (Koohestani, 2019), where the system is relatively well functioning, only the sensory-motor factor (sending SMS) was considered as distracted state. In the study (McDonald, 2020), which considered two sensory-motor and cognitive factors as distracted state, the system did not have a high ACC. Only in the article by Panagopoulos et al. all three types of sensory-motor, cognitive and emotional distractions were used and the relatively low ACC was achieved. In this study, the leave one subject out cross validation was used to evaluate the system performance. This generalizable method does not include any kind of information from test subject in training data set. So, the system is designed independent from subjects. The performance of the proposed method outperformed the previous studies while they (Panagopoulos, 2019) did not evaluate the system using subject independent classifiers. It should be noted that in most studies, complex algorithms have been used to classify the distraction state, while we used simple classifiers in machine learning context. The main reason of increasing performance of the proposed distraction detection system is applying useful and informative features especially functional connectivity between physiological and thermal signals. We used these connectivity features for the first time, which led to higher ACC of distraction detection. The ACC obtained in this study (99.16%) was the average ACC of 58 subjects obtained by the LOSO validation method. We investigated statistically significant difference between this result and the last study that considers three types of distractions as distracted class vs. normal state. There was a significant difference between the accuracy of this study and the latest one ($P<0.001$).

Our contribution, beside the proposed functional connectivity features, was introduction of distraction detection systems with acceptable performances. We could discriminate the types of distractions upper than chance level. Therefore, it can be concluded that there is useful and complementary information in the connectivity between physiological signals of drivers (BR, HR) and the quantified signal of perinasal perspiration index extracted from thermal images (PP) to detect and recognize driver distraction. This recognition can enhance the ability of automatic systems in driver industry in order to detect the state of drivers and make preferred suggestions.

As future work, we plan to use other signals from the simulator dataset, such as steering angle, acceleration, speed, left and right eye diameter and facial expressions signals, and calculate the connectivity between them. The features extracted from behavioral signals like steering angle, acceleration and speed are good indicators of sensory-motor distractions. As another suggestion, one can calculate the short-time prediction of driver distraction. Reference (Panagopoulos, 2019) was the only study that predicted driver distraction. It is plausible to improve the distraction prediction using the connectivity features. Another suggestion is using the frequency domain features along with the classic and temporal functional connectivity features to improve the performance of the system.

Declaration of Competing Interest

The authors proclaim that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Distracted driving recognition based on functional connectivity analysis between physiological signals and perinasal perspiration index

Nilufar Vosugh[a], Zahra Bahmani*[b], Amin Mohammadian [c]

[a] Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, V.nilufar@modares.ac.ir.

[b] Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, z.bahmani@modares.ac.ir.

[c] Research Center for Development of Advanced Technologies, Post Code:1114112312, mohammadian@rcdat.ir, Tehran, Iran.

** Corresponding author.*

Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, *Email address: z.bahmani@modares.ac.ir, phone number: 00989127252354.*

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Nilufar Vosugh[a], Zahra Bahmani*[b], Amin Mohammadian [c]

[a] Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, V.nilufar@modares.ac.ir.

[b] Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, z.bahmani@modares.ac.ir.

[c] Research Center for Development of Advanced Technologies, Post Code:1114112312, mohammadian@rcdat.ir, Tehran, Iran.

** Corresponding author.*

Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran, Post Code: 1411713116, *Email address: z.bahmani@modares.ac.ir, phone number: 00989127252354.*

ABSTRACT

Automatic detection of distracted driving is essential to ensure safety of drivers. In this paper, a novel set of features were extracted from thermal and physiological signals in order to detect and recognize distraction of drivers. Thermal video data which measured the temperature of different areas of the face, heart rate, breathing rate and behavioural signals were used while various types of distractions including cognitive, emotional and sensory-motor were applied to the subjects. The proposed discriminator features were extracted by different functional connectivity methods between the perinasal perspiration extracted from thermal images of the face and physiological variables of heart rate and breathing rate. After feature extraction, binary classification methods were applied to detect the distractions. The results showed that using functional connectivity features significantly increases the accuracy of distraction detection system (99.16%). Hence, the proposed model significantly improved (P<0.001) the detection of distraction compared to previous studies. Furthermore, we used the same feature set to recognize different types of distractions by using three-class classifiers. The suggested methods distinguished three types of distractions with the best accuracy of 81.94% related to cognitive, sensory-motor distraction and no-distraction states. We also tried to discriminate two types of cognitive distractions, analytic and mathematical distractions. The recognition system classified two types of cognitive distractions with an accuracy of 91.78%. The results suggest that there is important and complementary information in the connectivity between facial temperature signals and physiological variables for distraction detection and recognition.

Keywords: Functional connectivity, driving distractions, physiological signals, facial thermal images.

1. Introduction

Distracted driving is a condition that the driver's attention is diverted to other tasks over a period of time. Using a mobile phone or immersing in thoughts and memories can lead to distraction. This disrupted driving involves a lot of financial and personal risks. According to the World Health Organization, in 2016, more than one million drivers lost their lives in accidents (Rana, 2021). As a result, paying attention to the distraction and trying to improve driver assistance systems are important and necessary, especially in today's world where science and technology are growing rapidly. If driver distraction is detected automatically, systems can alert the driver to return his/her focus to the road. This warning will reduce the consequences of driving distraction (Pavlidis, 2018). In general, distraction factors can be divided into three categories: cognitive, emotional and sensory-motor (Fatmi, 2019). Several studies have considered detection of driver distraction. Some of these studies have been performed in real-condition environments, in which the desired signals in the car environment were extracted under different conditions while driving (Osman, 2019; Zhao, 2020; Jain, 2021; Day, 2021; Alzubi, 2022; Huang, 2020). In most of these studies, only physical distraction factors (send SMS, call, drink, make up, …) were used and the best accuracy was 96.74%, published in 2020 (Huang, 2020). Driving simulators make it possible to monitor driving performance in a controlled and safe environment. So, many studies have been tried to understand the distracted driving mechanism using driving simulators (Taamneh, 2017; Tran, 2018; Zhang, 2021; Tango, 2013; Ma, 2022). The behavioral signals can be used for distraction detection (Ma, 2022). Besides, Physiological signals, visible and non-visible videos and brain signals included indicator indexes of distraction (Li, 2021; Fan, 2021; Liang, 2022, Day, 2021). Kian Hamedani et al. proposed a method for non-contact measurement of heart rate using thermal imaging (Hamedani, 2016). Pavlidis et al. recorded and shared a rich dataset of different kinds of signals during driving while different types of distractions including cognitive (CD), emotional (ED) and sensory-motor (MD) distractions were applied to drivers (Pavlidis, 2016). This dataset was called simulator study 1 that included a large number of subjects (Taamneh, 2017). In addition, the dataset considered all aspects that may cause driver distraction, and it is more comprehensive in terms of the number of subjects, age and gender in comparison with other studies (Tran, 2018; Zhang, 2021; Tango et al., 2013).

Using the mentioned dataset, several research works have been done with the two general purposes of statistical modeling of distraction (Pavlidis, 2016; Pavlidis, 2018; Gomez, 2018) and distraction detection systems (Panagopoulos, 2019; Tango et al., 2013; McDonald, 2020; Koohestani, 2019) which is also the purpose of this study. Panagopoulos and Pavlidis used a new algorithm called maximum gradient boosting. They extracted features from three variables including Breathing Rate (BR), Heart Rate (HR), and the Perinasal Perspiration (PP) signals extracted from thermal images and achieved 78.36% accuracy of distraction detection (Panagopoulos, 2019). In addition, Pavlidis et al. presented important results in the short-term prediction of dangerous driving behaviors. In another study detection of sensory-motor distraction of the driver was done by help of vehicle dynamics data with 96% performance (Tango et al., 2013).

McDonald et al. analyzed the physiological and behavioral datasets of drivers with 21 machine learning algorithms, which provided the highest accuracy (65%) using random forest method (McDonald, 2020). Koohestani et al. focused on analyzing driver performance with various machine learning techniques, they measured 97.50% accuracy of sensory-motor distraction detection (Koohestani, 2019).

As mentioned, distraction detection systems should be improved in terms of system's performance and consideration of different distraction factors. Mostly, studies in the field focused on, physical distraction factors (Wang, 2022), however, mental (emotional and cognitive) distraction factors are as dangerous as physical distractions (sensory-motor). Thus, introducing general distraction systems with high performances is necessary. Among recent studies on Pavlidis simulator dataset (Panagopoulos, 2019), the best accuracy was 78.36% for detecting distraction including all factors. Besides, distraction recognition system should be considered as a new module in these systems. Using distraction recognition systems, the types of distraction factors are also predicted. Distraction factors can be handled differently in real applications for drivers.

In general, the main purpose of this study is to improve the performance of the distraction detection system. A distraction recognition system is proposed which can discriminate all three types of distraction factors (mental and physical). We focused on the connectivity between physiological and thermal variables of the driver signals as a new informative approach. In Section 2, materials and methods are described in detail. The results are presented in Section 3 followed by conclusion in Section 4.

2. Material and methods

2.1. Task

Simulator study 1 dataset was obtained by Pavlidis group. We will briefly explain about the task and data. For complete details of the task and dataset, refer to Taamneh et al., 2017 and Pavlidis et al., 2016.

Using simulator driving, subjects drove several different sessions. The sessions were practice drive (PD), relaxing drive (RD), No-distracted drive (ND), cognitive distraction driving (CD), emotional distraction driving (ED) and sensory-motor distraction driving (MD). PD is designed to learn the environment of the simulator. In RD and ND, subjects drove without any distractions. Finally, drivers experienced driving with cognitive, emotional, and sensory-motor distractions. In this experiment each distraction session contained 5 phases. The defined distraction factor is only applied in phases 2 and 4 of each session. During phases 1, 3 and 5 no distraction was applied to the subjects. In our study, to detect distraction more closely, phases 2 to 4 in which the distraction factors were applied to the drivers were considered as distracted phases. The CD sessions had two different types of cognitive distraction factors that are called analysis and mathematical questions (CD_AQ, CD_MQ) applied in different phases (2 and 4). Here, only phases that the cognitive distraction factors were applied directly to the drivers were considered as distracted phases (phases 2 and 4). See references Taamneh et al., 2017 and Pavlidis et al., 2016 for further details of tasks and the dataset.

2.2. The general process of this study

To improve the performance of the distraction detection system, in this study we propose features based on connectivity analysis between physiological and thermal variables of driver signals. Fig. 1 shows the block diagram of the proposed method. First, desired driver signals were selected from Simulator Study 1 dataset. These variables were normalized using z-score formula 1. Then, the signals were segmented, classic and connectivity features were extracted from the signals. These features were used for training classification models and finally performance of the system was examined to detect driving distraction.

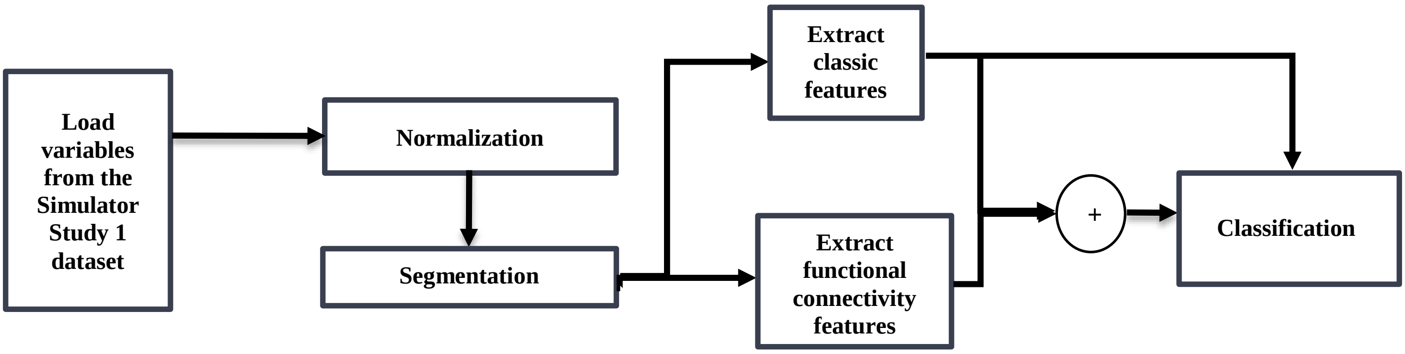


Fig. 1. Block diagram of the proposed method.

According to Fig. 2, some of the physiological and behavioral variables of drivers have been measured in the Simulator Study 1 dataset (Taamneh, 2017). We examined four signals including BR and HR as typical physiological variables of drivers, PP that is extracted from thermal images as thermal physiological and the Lane Offset (LO) as a behavioral variable. Contrary to physiological signals that were obtained from wearable sensors, PP is an arousal index of perinasal perspiration estimated by non-contact thermal camera.

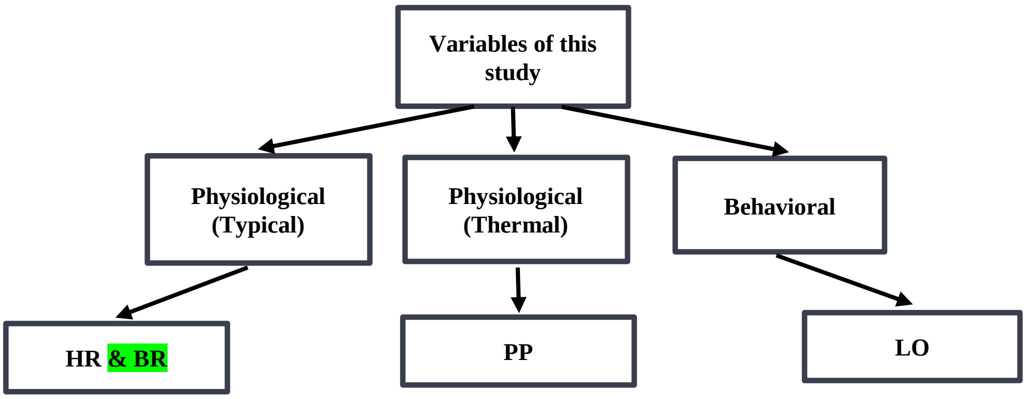


Fig. 2. Four variables from the three categories of signals used in this study. HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset.

According to the Simulator Study 1 dataset (Taamneh, 2017), it was not possible to extract PP of all subjects due to having facial hair in the area around the nose. Also, the BR signal of subject number 67 was not defined due to experimental problems. Therefore, we had signals of 58 subjects in this study.

2.3. Normalization

As preprocessing, we used a within subject normalization method called Z-Score (Equation 1). In this method, we subtracted each sample (*i*) of signal (*x*) from the average of samples (μ) and divided it by standard deviation (*S*). This process was applied on each signal for each subject separately.

$$Z_{Score} = (x_i - \mu)/\ S \tag{1}$$

2.4. Segmentation

In accordance with (Panagopoulos, 2019), the signals were segmented in windows of size 10 with 90% overlap between successive windows.

2.5. Feature extraction

We examined two types of feature sets, one of them was the classic feature set and the other one uses the features based on the connectivity of two signals. Both categories of features were defined in the time domain. We used connectivity features among physiological, thermal and behavioral signals in order to detect and recognize distraction for the first time in this field. These types of features have not been used in the previous studies. The purpose of defining classic features was to investigate the effect of connectivity features in improvement of the system performance. We divided the classic features into statistical and structural categories. Table 1 shows the types of these features. These statistical and structural features were extracted from 10 seconds time windows of the signals. As a result, 11 classic features were extracted from each time window of signals. Using 4 signals, we obtained 44 features from each time window of the classic feature set.

Table 1. Types of classic features: statistical and structural.

Statistical	Structural
Variance	**Maximum**
Median	**Minimum**
Standard deviation	**Maximum -Minimum**
Mode	**Skewness**
Mean	**Kurtosis**
Entropy	-

In the functional connectivity features, the connectivity between two signals was investigated. Since the non-contact signal (PP) was reported as an effective signal in detecting driver distraction (Panagopoulos, 2019Tango, 2013), PP has always been considered as one of the pairs for measuring connectivity. In general, 6 non-directional connectivity can be defined among these four signals. We performed our calculations from only 3 connections containing PP, shown in Fig. 3.

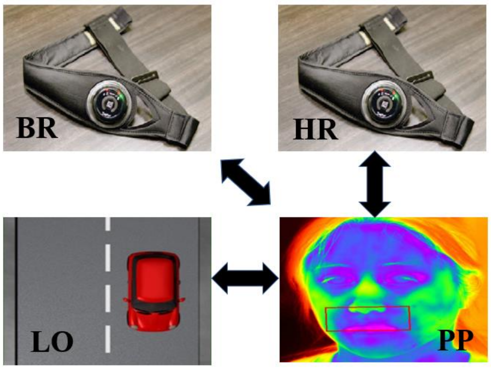


Fig. 3. Three non-directional functional connectivity containing PP were used (PP-BR), (PP-HR) and (PP-LO). HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset. (color should be used for this figure in print)

Functional connectivity which expresses the connectivity between two variables can be measured by different methods. Fig. 4 shows the methods of functional connectivity measurement used in this study.

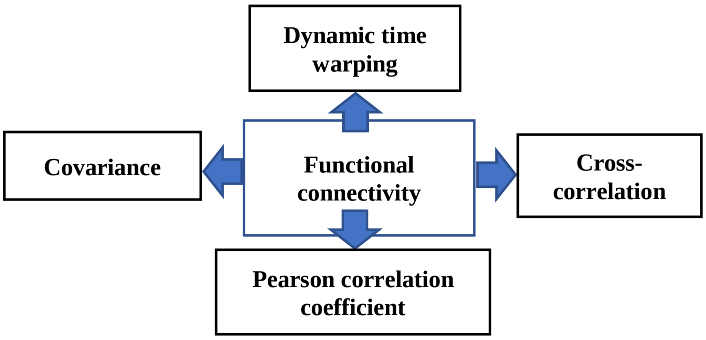


Fig. 4. Different methods of functional connectivity measurement used in this study.

Covariance and correlation can be mentioned as criteria for calculating the functional connectivity between two variables.

$$cov(x,y) = 1/(n-1)\sum_{i=1}^{n}(x_i - \mu_x)(y_i - \mu_y) \tag{2}$$

Equation 2 shows how the covariance (*cov*) of the two signals *x*, *y* is calculated from observations of each signal and the mean of the signals (μ_x, μ_y); n is the sample size and *i* is the index of each sample of signals. It shows what happens to *y* with changes in *x*, and vice versa. The correlation is a normalized covariance with values between 1 and -1. The correlation between the two signals were calculated as the correlation coefficient (Equation 3).

$$\rho_{xy} = cov(x,y)/\sqrt{\sigma_x^2 * \sigma_y^2} \tag{3}$$

In this equation *cov(x,y)* is the covariance between two signals *x,y* and σ_x^2, σ_y^2 are the variances of the two signals *x,y*, respectively. The correlation coefficient (ρ) between two variables (*x*, *y*) indicates the ability to predict the value of one variable from the other. Depending on the type of data, there are different ways to measure the correlation coefficient. In general, three types of correlation coefficients are defined: 1. Pearson 2. Spearman and 3. Kendall correlation coefficient. One of the most usual ways to measure the dependence between two quantitative variables is to calculate the Pearson correlation coefficient. Using the Cauchy-Schwartz inequality, it can also be shown that the absolute value of the correlation coefficient will never be greater than one.

Cross-correlation between two signals was examined as another type of functional connectivity that deals with the similarity of two signals (Yoo, 2009). Here, Cross-correlation was used to calculate the connectivity features, which is the product of the internal multiplication of two signals. The Cross-correlation of two signals of length 10*1 has 19 samples, and because we defined one feature for each time window, we used the maximum, minimum and mean values of these 19 samples as functional connectivity features.

Dynamic time warping calculates the statistical distance between two signals. This time domain algorithm extends the two vectors from the window samples of both signals over a set of common moments, so that the sum of the Euclidean distances between the corresponding regions is the smallest value.

Three lines of connectivity were defined between PP and BR, PP and HR, as well as between PP and LO. For each pair of signals, 6 functional connectivity features were extracted using the mentioned methods. Totally, we had 18 connectivity features from each time window of signals. Next, we examined the driver distraction detection by machine learning methods using these 62 features (44 classic and 18 connectivity features). we had 161755 samples of all windows for distracted detection and normal classes.

The extracted features were monitored and the non-informative features were excluded. The criteria of excluding features were: 1. The variance of the features was less than 0.001. 2. The sum of the samples of those features was zero. 3. Existence of very large values in the feature vectors. All feature vectors were normalized to mean 'zero' and variance 'one'.

2.6. Classification

We designed a binary classifier for the distraction detection system and several multi-class classifiers for the recognition systems. In the detection system, two-class mode of driver distraction was considered (distracted driving vs. normal driving). In the recognition systems, three-class modes (CD, ED, ND; CD, MD, ND; ED, MD, ND) and four-class mode were focused (CD, ED, MD and ND). In the Following, the detailed description of detection and categorization systems is explained.

Distraction detection system: First, we combined all three types of CD, ED and MD sessions into a class called distracted class and considered the ND, RD and PD sessions as the normal class. In the next step, we classified distracted and normal classes. We used Naive Bayes as the basic classification method for distraction detection. Bayesian classifier was used as a machine learning method to model the distraction detection system. Bayesian classifier has an acceptable speed and accuracy for this huge dataset (Taamneh, 2017). Besides, the systems were modeled with Support Vector Machines (SVM) and K-Nearest Neighborhood (KNN) methods. In previous studies, mostly one distraction factor has been considered as distracted driving class. Here, we also designed binary classifiers for detecting each distracted driving from no-distracted drive (ND vs. CD, ND vs. ED, ND vs. MD). The purpose was to know how we can detect each factor of distraction from ND and to be able to justify the superiority of the proposed method over other methods and studies. It should be noted that only in the first case of binary class (considering all combined distraction factors as distracted driving class), three sessions of ND, RD and PD were considered as the normal one. In other cases, in order to keep balance of sample sizes among classes, only ND session was considered as the normal class.

The inputs of classifiers in the detection system were features extracted from all pairs of signals (BR-PP, HR-PP, LO-PP). Also, in order to separately analyze the effect of each distraction factor on each signal, distraction detection systems were trained using features extracted from only one pair of signals.

Distraction recognition system (three-class mode): The purpose of this section was to investigate the separability of different distracted factors with each other (in the absence of the third factor). We trained different three-class systems in order to recognize the types of distraction factors besides detecting distraction. Cognitive distractions, which are considered as mental factors, were applied to the driver using two different stimuli. Firstly, analytical questions were asked by the experimenter, which required logical comparison, secondly, mathematical questions were asked from the driver and the subject had to do mental calculations. We studied this cognitive distraction factors in more detail. For this purpose, we designed a three-class cognitive recognition system (CD-AQ, CD-MQ, ND). We used Bayesian classifier in this mode.

Distraction recognition system (four-class mode): One of the innovations of this study compared to previous studies is investigating the discriminability of distraction factors using physiological, thermal and behavioural signals of drivers. Here, we trained a four-class classifier for recognition of the types of distractions (CD, ED, MD and ND). Bayesian classifier was used in this mode.

2.7. Leave One Subject Out cross validation (LOSO)

To evaluate how the machine learning model is generalized to a new subject, we used LOSO cross validation. In this method, we excluded the whole data of one subject from training dataset and considered the data of that subject as test dataset. Then, we trained the model with the training data set and then tested it with the test dataset. In this way the model is subject-independent and is more generalizable than k-fold cross-validation. This process was repeated 58 times (number of subjects), and the final performance was reported as the average performance of all subjects.

3. Results

In this section, the results are presented and analyzed. We modeled the distraction systems using two sets of classic and functional connectivity features. Among all the classic features extracted from driver signals, four categories of features were included according the exclusion criteria (The last paragraph of section 2.5). These features are mentioned in Table 2.

Table 2. Included sets of classic features which were used in this study. HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset.

All statistical features of BR, PP
All structural features of PP
Entropy of HR, LO
Max, min, max-min of BR

As shown in Table 2, all classical (statistical and structural) features of the PP signal passed the filter criteria and were considered as features for classification training.

3.1. Distraction detection system:

3.1.1. The impact of functional connectivity features on distraction detection system

We used different criteria to evaluate the classification algorithms. Accuracy (ACC) is the first and simplest criterion, which is equal to the number of cases we predicted correctly divided by the total number of observations. ACC is the main criterion of this research which has been mentioned in previous studies. In this study, all reported values of ACC are accuracy of the test dataset that were averaged from all epochs. F1 (Fisher-measure) is a type of average system ACC between the predicted data and the recall. The reason for choosing this criterion was the unequal number of samples in each class in some cases. Other criterion is Area Under the Curve (AUC) of Receiver Operating Characteristics (ROC). ROC is a graphical chart that shows the detection ability of a binary classification system. The larger the AUC, the more ideal.

In this part we used 44 classic features of all variables (BR, HR, LO, PP) and trained a Bayesian classifier as distraction detection model. As shown in Table 3, the ACC of detection between distracted and normal driving was 59.40% $(ACC_{distracted\ vs.\ normal} = 59.40\%, AUC_{distracted\ vs.\ normal} = 0.64, F1_{distracted\ vs.\ normal} = 0.28)$. After adding 18 functional connectivity features, the ACC of distraction detection reached 96.31% $(ACC_{distracted\ vs.\ normal} = 96.31\%, AUC_{distracted\ vs.\ normal} = 1, F1_{distracted\ vs.\ normal} = 0.96)$.

Table 3. Performance of Bayesian classification to detect driver distraction from normal case by using classic features and functional connectivity features.

Features	ACC (%)	AUC	F1
Classic	59.40	0.64	0.28
Classic + connectivity	96.31	1	0.96

In this case, more that 30% increase in ACC was obtained by using connectivity features. We used Wilcoxon signed rank test for investigating statistically significant differences of performance measurements between classic and total feature sets of Table 3. There was statistically significant difference between ACC of classic features and ACC of classic and connectivity (total) features (P<0.001). There was statistically significant difference between AUC of classic and total features (P<0.001), and there was statistically significant difference between F1 of classic features and F1 of total features (P<0.001). This analysis shows that, the performance of the distraction detection system after adding connectivity features was significantly enhanced. These results indicate that new and complementary information exists in the connectivity between physiological, thermal and behavioral signals. Fig. 5 demonstrates the bar plot of the ACC of the detection system for each subject using classic features (red lines) and both classic and functional connectivity features (blue lines). In this figure, the ACC of each subject is plotted (note that no information of this subject was observed by trained model). As mentioned in section 2.7 the validation method is LOSO, the final ACC was calculated by averaging ACC of each test subject.

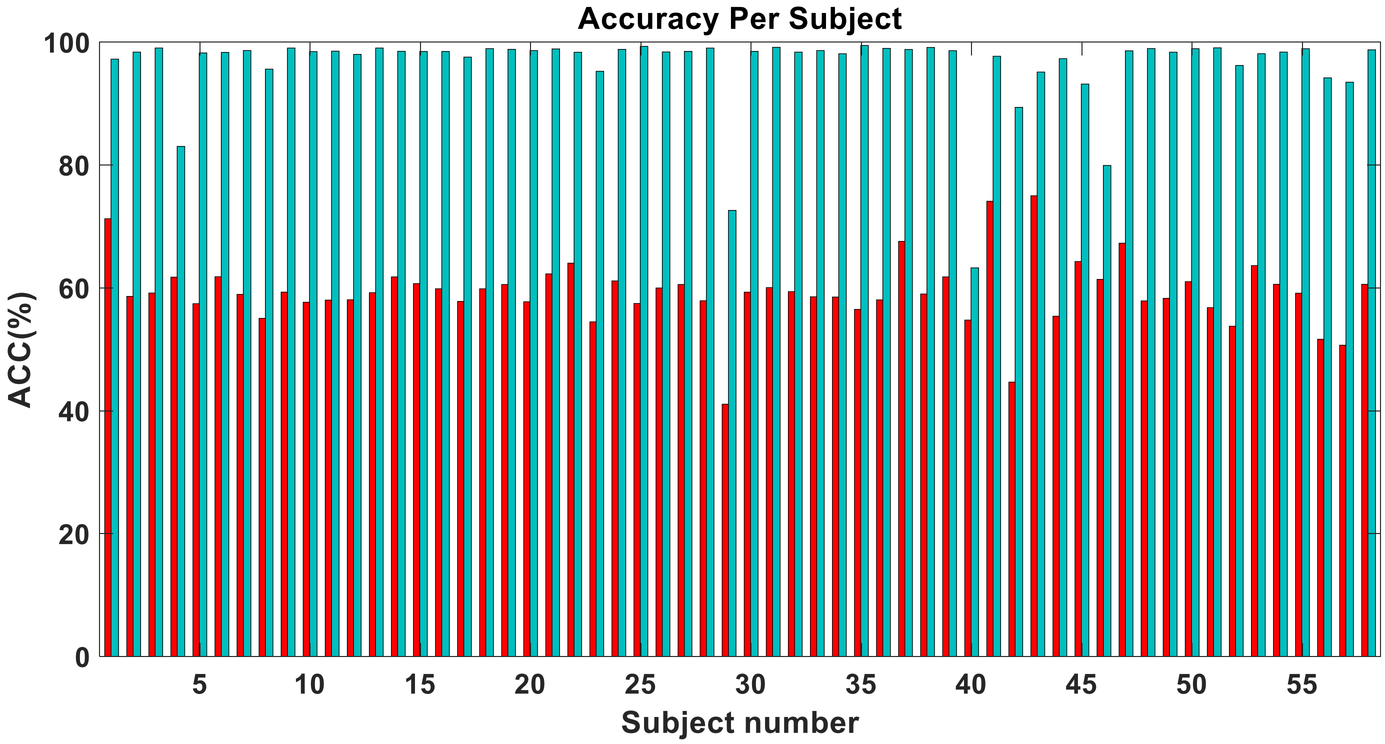
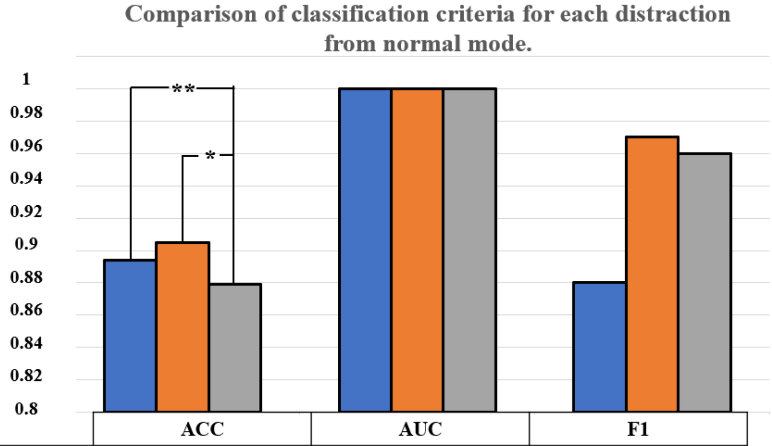


Fig. 5. Bar plot of the accuracy (ACC) of each subject in distraction detection system: classification ACC, using classic features (red), adding connectivity features (blue). (color should be used for this figure in print)

Fig. 5 shows the effectiveness of the functional connectivity features for each subject. All 58 subjects showed noticeable improvement in ACC of distraction detection.

3.1.2. The difference of distraction factors in detection system

In Fig. 6 distraction detection system was evaluated based on each distraction factor separately. Using total features (classic + connectivity), we obtained 89.38% ACC of detection between CD and ND, 90.47% ACC of detection system between ED and CD and 87.89% ACC of detection system between MD and ND ($ACC_{ND\ vs.\ CD} = 89.38\%, AUC_{ND\ vs.\ CD} = 1, F1_{ND\ vs.\ CD} = 0.88, ACC_{ND\ vs.\ ED} = 90.47\%, AUC_{ND\ vs.\ ED} = 1, F1_{ND\ vs.\ ED} = 0.97, ACC_{ND\ vs.\ MD} = 87.89\%, AUC_{ND\ vs.\ MD} = 1, F1_{ND\ vs.\ MD} = 0.96$).



	ACC	AUC	F1
ND-CD	0.8938	0.99	0.88
ND-ED	0.9047	0.99	0.97
ND-MD	0.8789	0.99	0.96

Fig. 6. Results of Bayesian classification to detect each distraction factors (CD=Cognitive Drive, ED=Emotional Drive and MD=sensory-Motor Drive) from ND (No-distracted Drive) using all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

The results showed that the ED with the highest ACC and F1 was the most detectable factor from the no-distraction mode.

We used Wilcoxon sign rank test for investigating significant differences between mental and physical distractions. There was statistically significant difference between ACC of ND_MD as the physical distractor and ND_ED as the mental distraction (P<0.001). Also, there were statistically significant difference between ND_MD as the physical distractor and ND_CD as the mental distraction (P=0.015). As a result, this connectivity feature set could detect mental distraction better than the physical one.

3.1.3. The impact of different signals in detection system

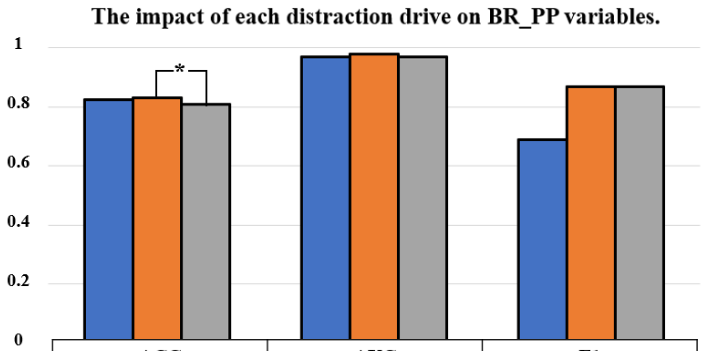
System performance using all three pairs of PP-HR, PP-BR, and PP-LO for feature extraction and classification were examined. The purpose of this analysis, as shown in Table 4, was to distinguish the most useful and informative pair of signals mentioned in the distraction detection system. We obtained 93.72% ACC of detection between distracted vs. ND for just features extracted of BR, PP signals with 6 connectivity and 22 classic features $(\mathrm{ACC}_{\mathrm{BR-PP,\ distracted\ vs.\ ND}} = 93.72\%, AUC_{\mathrm{BR-PP,\ distracted\ vs.\ ND}} = 0.99, F1_{\mathrm{BR-PP,\ distracted\ vs.\ ND}} = 0.92)$. 92.13% ACC of detection system between distracted vs. ND for just features extracted of HR, PP signals $(\mathrm{ACC}_{\mathrm{HR-PP,\ distracted\ vs.\ ND}} = 92.13\%,\ AUC_{\mathrm{HR-PP,\ distracted\ vs.\ ND}} = 0.98, F1_{\mathrm{HR-PP,\ distracted\ vs.\ ND}} = 0.91)$ and 60.02% ACC of detection system between distracted vs. ND for just features extracted of LO, PP signals were achieved. $(\mathrm{ACC}_{\mathrm{LO-PP,\ distracted\ vs.\ ND}} = 60.02\%, AUC_{\mathrm{LO-PP,\ distracted\ vs.\ ND}} = 0.90, F1_{\mathrm{LO-PP,\ distracted\ vs.\ ND}} = 0.66)$.

Table 4. Bayesian classification results of distraction detection using coupling variables. HR: Heart rate, BR: Breathing rate, PP: Perinasal perspiration and LO: Lane offset.

connectivity	ACC (%)	AUC	F1
BR-PP	93.72	0.99	0.92
HR-PP	92.13	0.98	0.91
LO-PP	60.02	0.90	0.66

In this case, we used both the classic and the functional connectivity features associated with each pair of variables. We investigated statistically significant differences among the ACC of distraction detection system using BR-PP, HR-PP and LO-PP pairs of signals with non-parametric Friedman test. There was significant difference among ACC of BR_PP, HR_PP and LO_PP ($\mathrm{ACC}_{\mathrm{BR-PP,\ distracted\ vs.\ ND}} = 93.72\% \pm 3.0074,\ \mathrm{ACC}_{\mathrm{HR-PP,\ distracted\ vs.\ ND}} = 92.13 \pm 0.9081,\ \mathrm{ACC}_{\mathrm{LO-PP,\ distracted\ vs.\ ND}} = 60.02 \pm 5.3140 * 10^{-5}$, P<0.001). Using Friedman test, there was significant difference among the AUC of these three groups of signals (P<0.001). Also, there was significant difference among the F1 of these three groups of signals (P<0.001). For calculating the significant difference between two of them, we used non-parametric Posthoc Nemenyi test. The ACC (P<0.001) and F1 (P<0.001) of BR_PP and LO_PP were significantly different and the ACC (P<0.001) and F1 (P<0.001) of HR_PP and LO_PP were also significantly different. But the ACC (P=0.742) and F1(P=0.301) of BR_PP and HR_PP wasn't significantly different. The AUC of BR_PP and LO_PP (P<0.001), HR_PP and LO_PP (P<0.001) was significantly different. Also, the AUC of BR_PP and HR_PP was significantly different (P<0.001). As a result, the connectivity between BR_PP and HR_PP were informative pairs of signals for distraction detection. According to the results of Table 4, BR_PP seems to contain more information than all other pairs of signals. In all three performance measurements, BR_PP performed significantly better than LO_PP. But compared to the HR_PP, only the F1 criterion was significantly higher. However, ACC and AUC using BR_PP was higher than that of HR_PP, the differences were not statistically significant.

Fig. 7 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on BR_PP variables. We obtained 82.58% ACC of detection between CD and ND $(ACC_{ND\ vs.\ CD} = 82.58\%, AUC_{ND\ vs.\ CD} = 0.97\ and\ F1_{ND\ vs.\ CD} = 0.69)$, 82.94% ACC of detection between ED and ND $(ACC_{ND\ vs.\ ED} = 82.94\%, AUC_{ND\ vs.\ ED} = 0.98\ and\ F1_{ND\ vs.\ ED} = 0.87)$ and 80.97% ACC of detection between MD and ND for just features extracted of BR, PP signals $(ACC_{ND\ vs.\ MD} = 80.97\%, AUC_{ND\ vs.\ MD} = 0.97\ and\ F1_{ND\ vs.\ MD} = 0.87)$.

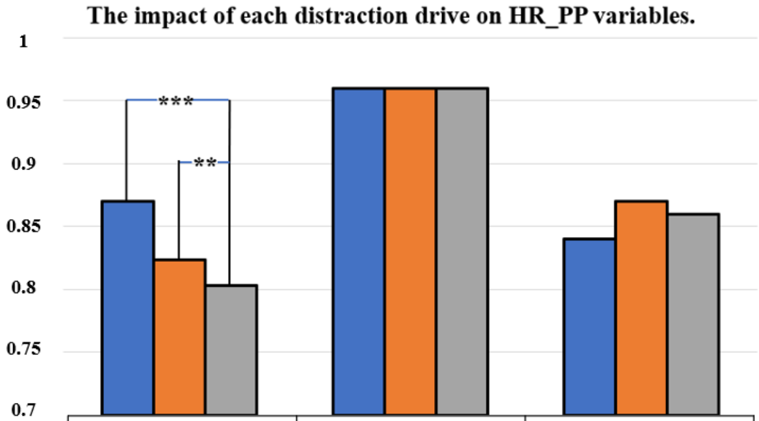


	ACC	AUC	F1
ND-CD	0.8258	0.97	0.69
ND-ED	0.8294	0.98	0.87
ND-MD	0.8097	0.97	0.87

Fig. 7. Results of Bayesian classification for BR_PP as a paired connectivity variables with all classic and connectivity features. BR: Breathing rate, PP: Perinasal perspiration. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

Fig. 7 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for compression. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There wasn't any significant difference between ACC of the system for classifying MD as physical distractor and CD as mental distractor from normal state in this case (P=0.439). There was significant difference between ACC of the system for classifying MD as physical distractor and ED as mental distractor from normal state in this case (P<0.001).

Fig. 8 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on HR_PP variables. We obtained 86.96% ACC of detection between CD and ND $(ACC_{ND\ vs.\ CD} = 86.96\%, AUC_{ND\ vs.\ CD} = 0.96\ and\ F1_{ND\ vs.\ CD} = 0.84)$, 82.33% ACC of detection between ED and ND $(ACC_{ND\ vs.\ ED} = 82.33\%, AUC_{ND\ vs.\ ED} = 0.96\ and\ F1_{ND\ vs.\ ED} = 0.87)$ and 80.27% ACC of detection between MD and ND for just features extracted of BR, PP signals $(ACC_{ND\ vs.\ MD} = 80.27\%, AUC_{ND\ vs.\ MD} = 0.96\ and\ F1_{ND\ vs.\ MD} = 0.86)$.



	ACC	AUC	F1
ND-CD	0.8696	0.96	0.84
ND-ED	0.8233	0.96	0.87
ND-MD	0.8027	0.96	0.86

Fig. 8. Results of Bayesian classification for HR_PP as a pair of connectivity variable with all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***) HR: Heart rate, PP: Perinasal perspiration. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive (color should be used for this figure in print)

Fig. 8 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for comparison. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There was significant difference between system performances for classifying ED as mental and MD as physical distractions from normal state in this case (P<0.01). There was significant difference between system performances for classifying CD as mental and MD as physical distractions from normal state in this case (P<0.05).

Fig. 9 demonstrates the impact of each distraction drive (ND_CD, ND_ED and ND_MD) on LO_PP variables. We obtained 85.23% ACC of detection between CD and ND $(ACC_{ND\ vs.\ CD} = 85.23\%, AUC_{ND\ vs.\ CD} = 0.96\ and\ F1_{ND\ vs.\ CD} = 0.84)$, 84.89% ACC of detection between ED and ND $(ACC_{ND\ vs.\ ED} = 84.89\%, AUC_{ND\ vs.\ ED} = 0.98\ and\ F1_{ND\ vs.\ ED} = 0.91)$ and 81.83% ACC of detection between MD and ND for just features extracted of BR, PP signals $(ACC_{ND\ vs.\ MD} = 81.83\%, AUC_{ND\ vs.\ MD} = 0.98\ and\ F1_{ND\ vs.\ MD} = 0.88)$.

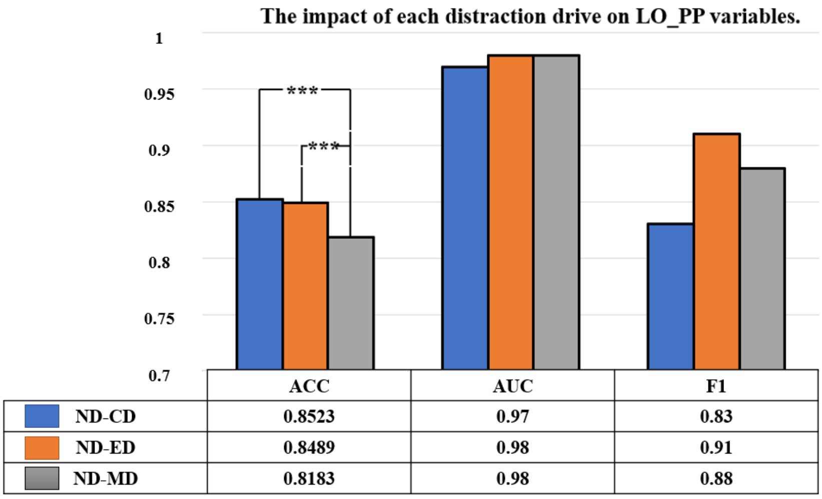


Fig. 9. Results of Bayesian classification for LO_PP as a pair of connectivity variable with all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). PP: Perinasal perspiration and LO: Lane offset. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive (color should be used for this figure in print).

Fig. 9 shows that ACC of the distraction detection system was the most for discrimination between ND and CD states. However, due to unbalancing of two classes CD and ND, F1 was the better criteria for comparison. Accordingly, ND and ED states were classified with the best performance in this section. We used Wilcoxon sign rank as a non-parametric test between performances of physical distraction detection system (MD) and mental distraction detection systems (CD and ED). There was significant difference between system performances for classifying ED as mental and MD as physical distractions from normal state in this case (P<0.05). There was significant difference between system performances for classifying CD as mental and MD as physical distractions from normal state in this case (P<0.05).

As a result of Fig. 7, Fig. 8 and Fig. 9 ACC of the distraction detection system was the most for discrimination between ND and CD states. For HR-PP and LO-PP variables, the ACC of the physical (MD) and mental (ED and CD) distraction detection system was significantly different. The results show that emotional and cognitive factors have the greatest impact on modulating all three pairs of variables. Thus, connectivity features are effective in identifying the causes of mental distraction. Obviously, physical distraction mostly modulates behavioral variables such as steering angle and gaze position which are not considered in this study as we focused on detecting distraction from physiological states of body and brain.

3.2. Distraction recognition system (three-class):

3.2.1. *Separability of different distraction factors*

The purpose of this section is to test the discriminability of different kinds of distraction states. We performed the three-class classification in order to investigate how different distraction factors modulate physiological signals of drivers. As shown in Table 5, All classic and connectivity features were extracted from three pairs of PP-HR, PP-BR, and PP-LO signals. The AAC of 81.55% were obtained for recognition among ND, CD, ED classes ($ACC_{ND,CD,ED} = 81.55\%, F1_{ND,CD,ED} = 0.84$). ND, CD, MD classes were recognized with 81.94% ACC ($ACC_{ND,CD,MD} = 81.94\%, F1_{ND,CD,MD} = 1$) and ND, CD, MD were classified with 66.42% ACC ($, ACC_{ND,ED,MD} = 66.42\%$).

Table 5. Results of three-class distraction recognition system. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive

Classes	ACC (%)	F1
ND, CD. ED	81.55	0.84
ND, CD, MD	81.94	1
ND, ED, MD	66.42	-

We investigated statistically significant difference among the ACC of the three-classes classifiers with non-parametric Friedman test. There were a significant difference among ACC of ND_CD_ED, ND_CD_MD and ND_CD_MD recognition systems ($ACC_{ND,CD,ED} = 81.55 \pm 2.6561, ACC_{ND,CD,MD} = 81.94 \pm 2.5203 \; and \; ACC_{ND,ED,MD} = 66.42 \pm 1.8937$, P<0.001). For calculating the significant difference between two of them, we used non-parametric Posthoc Nemenyi test. The ACC of ND-CD-ED and ND-CD-MD recognition systems was significantly different (P=0.002). The ACC of ND-CD-ED and ND-ED-MD recognition systems was significantly different (P<0.001). Also, there was significant difference between ACC of ND-CD-MD and ND-ED-MD recognition systems (P<0.001). Sensory-motor and cognitive distractions were separated with the highest ACC percentage. Fig. 10 shows the confusion matrix of all three states of Table 5.

(94.21%) 35510	**(1.21%)** 458	**(4.57%)** 1723
(2.23%) 353	**(52.85%)** 8367	**(44.91%)** 7109
(4.23%) 1172	**(2.71%)** 751	**(93.05%)** 25757

(a)

(94.92%) 35780	**(0.89%)** 336	**(4.17%)** 1575
(2.17%) 345	**(53.55%)** 8477	**(44.26%)** 7007
(3.26%) 913	**(4.09%)** 1146	**(92.64%)** 25931

(b)

(96.17%) 36248	**(0.48%)** 183	**(3.34%)** 1260
(2.99%) 830	**(21.11%)** 5844	**(75.88%)** 21006
(3.10%) 869	**(16.85%)** 4718	**(80.03%)** 22403

(c)

Fig. 10. Confusion matrixes of the different three-class recognition system. a) Confusion matrix of recognition system among ND, CD, ED. b) Confusion matrix of recognition system among ND, CD, MD. c) Confusion matrix of recognition system among ND, MD, ED. (color should be used for this figure in print)

As a result, in Fig. 10 a, b shown, the proposed recognition system had low performance to recognize CD distractor and the same pattern was observed for MD distractor recognition in Fig. 10 c.

3.2.2. Discriminability of different types of cognitive distractions

In this section, we study the cognitive factors in more detail. The cognitive distraction factors were applied to subjects by the experimenter using two different categories of analytical and mathematical questions. We want to discriminate these two types of cognitive distraction states and the no-distracted state. For one of the subjects, only the results of the analysis questions were presented in the data set, so this subject is excluded from analysis and the results were measured from 57 drivers. AS shown in Table 6, we obtained 91.78% ACC of recognition among CD_AQ, CD_MQ, ND ($ACC_{ND,CD-AQ,CD-MQ} = 91.78\%, F1_{ND,CD-AQ,CD-MQ} = 0.93$).

Table 6. Results of recognition among two different types of cognitive distraction, mathematical questions (CD_MQ = CD1) and analytical questions (CD_AQ = CD2) and no-distraction (ND).

Classes	ACC (%)	F1
ND, CD1, CD2	91.78	0.93

In mathematical questions, subjects should mentally perform a series of operations of addition and subtraction of multi-digit numbers, while in analytical questions, different logical and analytical questions were answered by drivers.

3.3. Distraction recognition system (four-class)

In this step, we examine the discriminability of four-class states including three types of distraction and no-distraction states. The result of the classifier performance is presented in Table 7. We obtained 63.39% ACC of recognition among ND, CD, ED, MD using all classic and connectivity features ($ACC_{ND\ vs.\ CD\ vs.\ ED\ vs.\ MD} = 63.39\%, F1_{ND\ vs.\ CD\ vs.\ ED\ vs.\ MD} = 0.65$).

Table 7. Results of Bayesian classification to recognize types of distraction (four-classes). CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive

Classes	ACC (%)	F1
ND, CD, ED, MD	63.39	0.65

In this section we could recognize types of distractions in three-class (P<0.001) and four-class (P<0.001) states with an accuracy significantly more than chance level. In Fig. 11, the confusion matrix is demonstrated. It should be noted that this ACC is the average ACC of 58 subjects.

(95.81%) 36113	**(0.66%)** 249	**(1.52%)** 573	**(2%)** 756
(1.83%) 290	**(52.83%)** 8364	**(26.77%)** 4239	**(18.54%)** 2936
(3%) 833	**(2.72%)** 753	**(40.32%)** 11161	**(53.94%)** 14933
(2.68%) 751	**(3.67%)** 1030	**(34.72%)** 9719	**(58.91%)** 16490

Fig. 11. Confusion matrix of the four-class recognition system (ND, CD, MD, ED). (color should be used for this figure in print)

Fig. 11 visualizes and summarizes the performance of the recognition system. The results show that emotional distraction have been detected with highest ACC among other distractions. The main reason of not achieving perfect classifier performance (Table 7) is distraction confusion.

3.4. Comparison of distraction detection system using other classifiers

In this section we tried to compare the performance of the proposed method with previous studies. First of all, the distraction detection system is trained with proposed features using different classifiers. The results of the distraction detection systems using other classifiers including SVM and the 5-nearest neighborhood and Bayesian are demonstrated in Fig. 12. We achieved the ACC of 96.31% for detection between distracted and normal driving with Bayesian classifier $\left(ACC_{distracted\ vs.\ normal,\ Bayesian} = 96.31\%, AUC_{distracted\ vs.\ normal,\ Bayesian} = 1, F1_{distracted\ vs.\ normal,\ Bayesian} = 0.96\right)$. We obtained 97.25% ACC of distraction detection using KNN classifier $(ACC_{distracted\ vs.\ normal,\ KNN} = 97.25\%, AUC_{distracted\ vs.\ normal,\ KNN} = 0.98, F1_{distracted\ vs.\ normal,\ KNN} = 0.97)$ and 99.16% ACC of distraction detection system by SVM classifier $\left(ACC_{distracted\ vs.\ normal,\ SVM} = 99.16\%, AUC_{distracted\ vs.\ normal,\ SVM} = 1, F1_{distracted\ vs.\ normal,\ SVM} = 0.99\right)$.

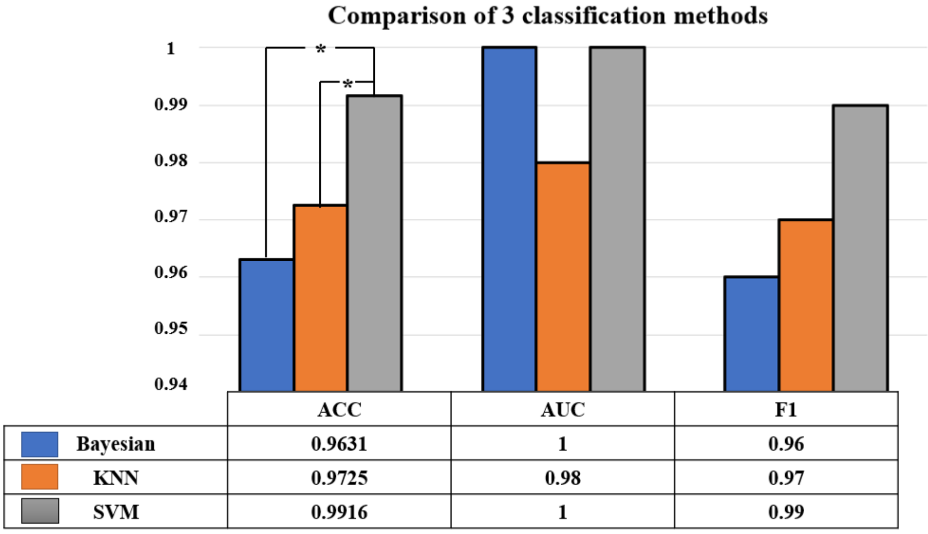


Fig. 12. Comparison of distraction detection system based on Bayesian, KNN and SVM classifiers using all classic and connectivity features. Wilcoxon sign rank test was used for checking significant differences (α=0.001 designated by *, α=0.01 designated by ** and α=0.05 designated by ***). (color should be used for this figure in print)

Fig. 12 shows that ACC of the distraction detection system was the most for detection by SVM classification. We used Wilcoxon sign rank as a non-parametric test between ACC of SVM classification model and ACC of KNN, Bayesian classification models. There was significant difference between ACC of SVM classification model and ACC of KNN classification model (P<0.001). There was significant difference between ACC of SVM classification model and ACC of Bayesian classification model (P<0.001). The results show that the highest performance of the system is related to the SVM classification with ACC of 99.16%. This study shows the importance of functional connectivity features between physiological signals and PP which significantly improved the ACC of the distraction detection system. A comparison with other studies using this data set is presented in Table 8.

Table 8. Comparison of driver distraction detection in previous studies with the proposed method. Factor 1: Physiological, 2: Behavioral and 3: Thermal signals. CD=Cognitive Drive, ED=Emotional Drive, MD=sensory-Motor Drive and ND=No-distracted Drive

Distracted factor	Method	ACC (%)	Input variables	Number of subjects	Reference
MD	Random forest	AUC=91	1+ 3	58	Koohestani et al., 2018
MD	GWO Algorithm	97.50	1 + 3	58	Koohestani et al., 2019
CD, MD	Random forest	65	1 + 2	48	McDonald et al., 2020
CD, ED, MD	XGB Algorithm	78.36	1 + 2 + 3	59	Panagopoulos et al., 2019
CD, ED, MD	**SVM**	**99.16**	**1 + 2 + 3**	**58**	**This study**

As shown in Table 8, in References (Koohestani et al., 2018) and (Koohestani et al., 2019), where the system is relatively well functioning, only the sensory-motor factor (sending SMS) was considered as distracted state. In the study (McDonald et al., 2020), which considered two sensory-motor and cognitive factors as distracted state, the system did not have a high ACC. Only in the article Panagopoulos et al. all three types of sensory-motor, cognitive and emotional distractions were used and the relatively low ACC was achieved. In this study, the LOSO cross validation was used to evaluate the system performance. This generalizable method does not include any kind of information from test subject in training data set. So, the system is designed independent from subjects. The performance of the proposed method outperformed the previous studies while they (Panagopoulos et al., 2019) did not evaluate the system using subject independent classifiers. It should be noted that in most studies, complex algorithms have been used to classify the distraction state, while we used simple classifiers in machine learning. The main reason of increasing performance of the proposed distraction detection system is applying useful and informative features especially functional connectivity between physiological and thermal signals. we used these connectivity features for the first time, which led to higher ACC of distraction detection. We achieved a higher level of ACC to detect the driver's distraction from the normal state than recent studies. The ACC obtained in this study (99.16%) was the average ACC of 58 subjects obtained by the LOSO validation method. We investigated statistically significant difference between this result and the last study that considers three types of distractions as distracted class vs. normal state. We used one-sample Wilcoxon sign rank test between 58 ACC of detection distracted by SVM and 78.36% ACC of Panagopoulos's study. There was a significant difference between the ACC of this study and the latest study ($P<0.001$).

The present study is comprehensive in terms of subject numbers and types of distraction factors. We also used three different types of signals: physiological (BR, HR), behavioral (LO), and thermal (PP) to detect driver distraction. Our innovation, beside the proposed connectivity features, was introduction of distraction recognition systems. For the first time, we could discriminate the types of distractions with acceptable performances. This recognition can enhance the ability of automatic systems in driver industry in order to detect the state of drivers and make preferred suggestions.

4. Conclusion and discussion

In this study we analyzed connectivity as a statistical measure of relationship between signals captured during driver's physiological and behavioral activities in order to extract features for distraction detection. For this evaluation, we modeled the distraction detection systems using two sets of classic (statistical and structural) and functional connectivity features. The ACC of detection between distracted and normal driving using classic features was 59.40%. After adding 18 functional connectivity features, the ACC of distraction detection reached 96.31%. There was statistically significant difference between ACC of classic features and ACC of total features ($P<0.001$). The analysis of the connectivity between the signals indicates a kind of coordinated and non-coordinated tone, which is an appropriate characteristic of changing drivers' mental states due to the presence of distractions. Then, the proposed distraction detection system was evaluated based on each distraction factor separately. As a result, in Fig. 6, the proposed connectivity feature set could detect mental distraction better than physical distraction. Also, we examined the proposed system performance using each pair of PP-HR, PP-BR, and PP-LO for feature extraction and classification. According to the results of Table 4, BR_PP seems to contain more information than all other pairs of signals. As a result of Figs. 7-9, ACC of the distraction detection system took the highest value for discrimination between

ND and CD states. For HR-PP and LO-PP variables, the ACC of the physical (MD) and mental (ED and CD) distraction detection systems was significantly different. The results show that emotional and cognitive factors have the greatest impact on modulating all three pairs of variables. Thus, connectivity features are effective in identifying the causes of mental distraction. Obviously, physical distraction mostly modulates behavioral variables such as steering angle and gaze position which are not considered in this study, as we focused on detecting distraction from physiological states of body and brain. We also performed the three-class classification in order to investigate how different distraction factors modulate physiological signals of drivers. As shown in Table 5, sensory-motor and cognitive distractions were separated with the highest ACC percentage. As a confusion result, presented in Fig. 10 a, b, the proposed recognition system had low performance to recognize CD distractor and the same pattern was observed for MD distractor recognition in Fig. 10 c.

The results in Fig. 12 show that the highest performance of the system is related to the SVM classification with ACC of 99.16%. As shown in Table 8, in references (Koohestani, 2018) and (Koohestani, 2019), where the system is relatively well functioning, only the sensory-motor factor (sending SMS) was considered as distracted state. In the study (McDonald, 2020), which considered two sensory-motor and cognitive factors as distracted state, the system did not have a high ACC. Only in the article by Panagopoulos et al. all three types of sensory-motor, cognitive and emotional distractions were used and the relatively low ACC was achieved. In this study, the leave one subject out cross validation was used to evaluate the system performance. This generalizable method does not include any kind of information from test subject in training data set. So, the system is designed independent from subjects. The performance of the proposed method outperformed the previous studies while they (Panagopoulos, 2019) did not evaluate the system using subject independent classifiers. It should be noted that in most studies, complex algorithms have been used to classify the distraction state, while we used simple classifiers in machine learning context. The main reason of increasing performance of the proposed distraction detection system is applying useful and informative features especially functional connectivity between physiological and thermal signals. We used these connectivity features for the first time, which led to higher ACC of distraction detection. The ACC obtained in this study (99.16%) was the average ACC of 58 subjects obtained by the LOSO validation method. We investigated statistically significant difference between this result and the last study that considers three types of distractions as distracted class vs. normal state. There was a significant difference between the accuracy of this study and the latest one ($P<0.001$).

Our contribution, beside the proposed functional connectivity features, was introduction of distraction detection systems with acceptable performances. We could discriminate the types of distractions upper than chance level. Therefore, it can be concluded that there is useful and complementary information in the connectivity between physiological signals of drivers (BR, HR) and the quantified signal of perinasal perspiration index extracted from thermal images (PP) to detect and recognize driver distraction. This recognition can enhance the ability of automatic systems in driver industry in order to detect the state of drivers and make preferred suggestions.

As future work, we plan to use other signals from the simulator dataset, such as steering angle, acceleration, speed, left and right eye diameter and facial expressions signals, and calculate the connectivity between them. The features extracted from behavioral signals like steering angle, acceleration and speed are good indicators of sensory-motor distractions. As another suggestion, one can calculate the short-time prediction of driver distraction. Reference (Panagopoulos, 2019) was the only study that predicted driver distraction. It is plausible to improve the distraction prediction using the connectivity features. Another suggestion is using the frequency domain features along with the classic and temporal functional connectivity features to improve the performance of the system.

Declaration of Competing Interest

The authors proclaim that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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