

DRIVING RISK COMPUTING DEVICE AND METHOD

FIELD OF INVENTION

[0001] The present invention relates to a computing device and method for
5 evaluating driving risk, and more particularly, a computing device and method
for driving behavior analysis, driver risk profiling and accident prevention.

BACKGROUND

[0002] Evaluating driving risk by analyzing patterns in GPS,
10 accelerometer, and G-force data helps to improve driving safety. Nowadays,
the information gathering and transmitting of vehicles is mostly done by
telematics devices, and the analyzed data is extensively employed by auto
insurance providers to assess drivers' behaviors and reconstruct accidents.
In the future of semi-autonomous or autonomous vehicles, the analytics data
15 from telematics can also be used for improving autonomous capability.

[0003] Current insurance telematics device, with data collected from GPS
and 3-axis accelerometer, is capable of speed monitoring, motion detection
and incident detection. However, despite of successful detection of certain
vehicle movements (e.g. hard braking, sudden turning), it may not be
20 sufficient to determine who is at fault in the event of an accident without
contextualization.

[0004] There is similar insufficiency when telematics data is used for
evaluating driving practice, mainly because GPS and 3-axis accelerometer

are not able to detect drivers' in-cabin movements such as signaling, blind spot checking or putting on seat belt. For insurance providers, information of these driving practices can be valuable to price the premiums of different drivers.

5 **[0005]** Thus, what is needed is a device and method that can evaluate driving risk by integrating data from GPS, accelerometer, camera video of vehicle's surrounding environment and in-cabin camera video. With a combined analysis and calculation of the data received from a vehicle, a score can be generated for the driving and the score can be used for driving
10 practice evaluation and accident prevention purposes.

SUMMARY

[0006] According to a first aspect, there is provided a computing device for evaluating driving risk. The computing device includes an input circuit
15 configured to receive data from a vehicle, the data comprising at least one of GPS data, acceleration data or image data. The computing device further includes a processor, and the processor is configured to train a situation classification model based on the data received from the vehicle using machine learning methods to classify various driving situations. The
20 processor is further configured to identify a plurality of risks based on the data received from the vehicle and one or more of the various driving situations classified by the situation classification model, determine a plurality of weightages wherein a respective weightage is assigned for each of the

plurality of risks, and generate a score based on the plurality of weightages for the plurality of risks.

[0007] According to a second aspect, there is provided a method for evaluating driving risk. The method includes: receiving data from a vehicle,
5 the data comprising at least one of GPS data, acceleration data and image data; training a situation classification model based on the data received from the vehicle using machine learning methods to classify various driving situations; thereafter identifying a plurality of risks based on the data received from the vehicle and one or more of the various driving situations classified
10 by the situation classification model; determining a plurality of weightages, wherein a respective weightage is assigned for each of the plurality of risks; and generating a score based on the plurality of weightages for the plurality of risks.

15 **BRIEF DESCRIPTION OF THE DRAWINGS**

[0008] The accompanying figures, where like reference numerals refer to identical or functionally similar elements throughout the separate views and which together with the detailed description below are incorporated in and form part of the specification, serve to illustrate various embodiments and to
20 explain various principles and advantages in accordance with a present embodiment.

[0009] FIG. 1 depicts an illustration of a computing device for evaluating driving risk in accordance with a present embodiment.

[0010] FIG. 2 depicts an illustration of a system for evaluating driving risk of a vehicle in accordance with the present embodiment.

[0011] FIG. 3 depicts a block diagram of a situation classification model in accordance with the present embodiment.

5 **[0012]** FIG. 4 depicts a block diagram of a manoeuver classification model in accordance with the present embodiment.

[0013] And FIG. 5 depicts a flowchart of steps involved in evaluating driving risk in accordance with the present embodiment.

[0014] Skilled artisans will appreciate that elements in the figures are illustrated for simplicity and clarity and have not necessarily been depicted to
5 scale. For example, the dimensions of some of the elements in the illustrations or diagrams may be exaggerated in respect to other elements to help to improve understanding of the present embodiments.

DETAILED DESCRIPTION

10 **[0015]** Embodiments of the present invention will be described, by way of example only, with reference to the drawings. Like reference numerals and characters in the drawings refer to like elements or equivalents.

[0016] Some portions of the description which follows are explicitly or implicitly presented in terms of algorithms and functional or symbolic
15 representations of operations on data within a computer memory. These algorithmic descriptions and functional or symbolic representations are the means used by those skilled in the data processing arts to convey most effectively the substance of their work to others skilled in the art. An algorithm is here, and generally, conceived to be a self-consistent sequence of steps
20 leading to a desired result. The steps are those requiring physical manipulations of physical quantities, such as electrical, magnetic or optical

signals capable of being stored, transferred, combined, compared, and otherwise manipulated.

[0017] Unless specifically stated otherwise, and as apparent from the following, it will be appreciated that throughout the present specification, 5 discussions utilizing terms such as “determining”, “computing”, “generating”, “processing”, “receiving”, “collecting”, “storing” or the like, refer to the action and processes of a computer system, or similar electronic device, that manipulates and transforms data represented as physical quantities within the computer system into other data similarly represented as physical 10 quantities within the computer system or other information storage, transmission or display devices.

[0018] Referring to FIG. 1, an illustration 100 of a computing device 10 for evaluating driving risk in accordance with a present embodiment is depicted. The computing device 10, which can be of a variety of types with the ability to 15 execute programmed instructions, includes an input circuit 12 and a processor 14 in the present embodiment. Although a single input circuit and a single processor are shown for the sake of clarity, the computing device 10 may also include multiple input circuits and a multi-processor system.

[0019] The input circuit 12 is configured to receive data 120 from a vehicle. 20 The data 120 may include GPS data 122, which can provide information of the location of the vehicle, the speed of the vehicle, the travelling distance and the travelling direction. The data 120 may also include acceleration data

124, which can be obtained from accelerometer (e.g., 3-axis accelerometer) of the vehicle. The acceleration data 124 can include accelerations that are linear or non-linear, in different directions or planes. The data 120 may further include image data 126. The image data 126 can be obtained from one or
5 more still cameras or video cameras placed in various locations of the vehicle. The image data 126 can be captured by the cameras with external views of surrounding environment outside the vehicle, including road condition, traffic condition, blind spot condition, weather condition, lighting condition and other vehicles. Additionally, the image data 126 also includes
10 images captured by the cameras with views inside the vehicle (e.g. in-cabin view). For non-autonomous vehicles where drivers are required, the cameras with views inside the vehicle can provide images of driver's postures and movements, such as head movements, hand movements or eye movements.

[0020] Referring to FIG. 2, an illustration of a system for evaluating driving
15 risk of a vehicle in accordance with the present embodiment is depicted. The devices in the vehicle for collecting the data 120 may include a GPS, 3-axis accelerometers, at least one camera with external views of surrounding environment outside the vehicle, and at least one camera with in-cabin view. In the present embodiment, the data 120 is further processed by a server 20.
20 As shown in the illustrated embodiment, the server 20 locates separately from the vehicle and can be remotely accessed via cloud. Alternatively, the server 20 can be located inside the vehicle where GPS data 122, acceleration data 124 and image data 126 are collected. Preferably, the

server 20 is connected to a communication bus to receive the data 120, which allows processing the real-time data collected from the vehicle. Alternatively, the data 120 may be stored in various forms of memory or storage medium (e.g., random access memory, read only memory, hard disk drive, removable storage drive) and processed at the server 20 subsequently.

[0021] Referring to FIG. 3, an illustration 300 of a block diagram of a situation classification model in accordance with the present embodiment is depicted. The data received from the vehicle is combined and processed to train the situation classification model. Preferably, different machine learning methods are used to efficiently train the situation classification model. As an example, computer vision methods, which can be traditional computer vision methods or deep learning methods (e.g. convolutional neural network), are used for processing the image data. Preferably, computer vision analysis of the image data from the camera with external views can provide information on traffic condition (e.g., slowing moving traffic), road condition (e.g., cross junction, zebra crossing, humps, slopes), weather condition (e.g., rain, snow) and other vehicle detection (e.g., vehicle driving in front, vehicle switching lane). Non-image data can be processed by other machine learning methods, such as random forest, support vector machines, linear regression, logistic regression, nearest neighbor and decision tree.

[0022] Other data collected from the vehicle, for example, GPS positions, vehicle speed, and manoeuvre / impact detection from the acceleration data and G-force data, are also used for the situation classification model. Data

collected from the vehicle may further include data from additional sensors or devices to provide a more comprehensive dataset, such as temperature data, humidity data, tire pressure or the like.

[0023] Based on all the data presented above, the situation classification model can be trained to classify various driving situations, including but not limited to one or more of the following: approaching a traffic light regulated junction, approaching a traffic sign regulated junction, approaching a non-regulated cross junction, approaching a non-regulated T junction, approaching a zebra crossing, turning from a major / minor road to a major / minor road, U-turning, reversing, lane changing in slow / fast moving traffic, overtaking in slow / fast moving traffic, overtaking along single carriageway, negotiating sharp bends, driving upslope / downslope, stopping upslope / downslope, moving off upslope / downslope, avoiding hazards to the vehicles to the front or to the side, entering / exiting highways, raining / snowing weather, and high / low visibility.

[0024] Referring to FIG. 4, an illustration 400 of a block diagram of a manoeuvre classification model in accordance with the present embodiment is depicted. The data received from the vehicle is combined and processed to train the manoeuvre classification model. Preferably, different machine learning methods are used to efficiently train the manoeuvre classification model. As an example, computer vision methods, which can be traditional computer vision methods or deep learning methods (e.g. convolutional neural network), are used for processing the image data. Preferably, for non-

autonomous vehicles where drivers are required, computer vision analysis from the camera with in-cabin view can provide information on the driver's head, hand and eye movements (e.g., checking blind spot, putting on seat belt, signaling).

5 **[0025]** Other data collected from the vehicle, for example, GPS positions, vehicle speed and manoeuvre / impact detection from the acceleration data and G-force data, are also used for the manoeuvre classification model. Based on all the data presented above, the manoeuvre classification model can be trained to classify various driver and vehicle manoeuvres, including
10 but not limited to one or more of the following: accelerating, braking, steering, signaling, engaging / releasing hand brake, checking rear view mirror, checking side view mirror, checking blind spot, putting on / taking off seat belt, and driving while distracted / intoxicated / drowsy / sleepy.

[0026] And referring to FIG. 5, a flowchart 500 of steps involved in a
15 method for evaluating driving risk in accordance with the present embodiment is depicted. At step 502, data is collected from the vehicle and received by the computing device. The data from the vehicle includes at least one of GPS data, acceleration data and image data. Other data from the vehicle that considered relevant to evaluating the driving risk may also be included, for
20 example, temperature data or data from additional sensors of the vehicle.

[0027] At step 504, a plurality of risks is identified based on the data received from the vehicle. The plurality of risks may include and not limited to

one or more of the following: not keeping a safe distance, not following traffic lights or traffic signs, not slowing down at road junctions, not signaling, not doing safety checks, and reckless driving. Identifying the risks is executed by the computing device, based on the data previously collected from the vehicle. More specifically, the computing device combines the outputs of the situation classification model and the manoeuvre classification model, and identifies a plurality of risks based on matching of the combined outputs. Optionally, there can be an integrated model at step 504 for processing the outputs from the situation classification model and the manoeuvre classification model.

[0028] The present disclosure of the method of identifying risks has the advantage of classifying more complicated driving scenarios and identifying driving risks more accurately, attributing to the situation classification model. For example, if the situation classification model shows the driver is driving on the highway in fast moving traffic, and the driver's vehicle is not close to the vehicle in front but there is a vehicle behind, the driver braking hard in this situation will be identified as a risk. Instead, if the situation classification model shows that the vehicle in front suddenly brakes hard, in this situation the driver braking hard while maintaining a safe distance to the vehicle in front will not be identified as a risk.

[0029] In another example, if the situation classification model shows the vehicle is approaching a traffic light junction and the traffic light is red, the driver accelerating will be identified as a risk of not following traffic light. In

another scenario, if the traffic light is amber, the driver accelerating may be identified as a risk of reckless driving.

[0030] The present disclosure of the method of identifying risks also has the advantage of incorporating driver's manoeuvres and identifying potential driving risks more effectively, attributing to the manoeuvre classification model. For example, if all the GPS data, acceleration data and image data from the camera with external view is showing the driver is driving safely on the road, but the camera with in-cabin view shows the driver does not have his seat belt on, it will be identified as a risk of not doing safety checks. Other examples include the camera with in-cabin view shows the driver is checking his phone frequently, the driver's eyes are not on the road, the driver is showing signs of intoxication / fatigue / distraction, the driver's posture is not safe for driving, and the driver is not signaling when turning or switching lane.

[0031] Each occurrence of the various risks identified will be logged and saved for generating a score of the driving risk later.

[0032] At step 506, a plurality of weightages is determined to assign a respective weightage for each of the risks. The weightages are user-defined and can be determined based on the severity of the risks or other factors depending on the interest of user. User of the computing device and method in the present disclosure can be insurance providers, police department, autonomous vehicle companies, the driver himself / herself, or the driver's family member / guardians.

[0033] Referring to the earlier example, the risk of not following traffic lights (accelerating when the traffic light is red) may get assigned a weightage of 5, and the risk of reckless driving (accelerating when the traffic light is amber) may get assigned a weightage of 3. For the same type of risk, 5 the weightages can be determined and assigned to reflect differences in severity, defined by the user. For example, speeding exceeding 15% of the regulated speed may get assigned a weightage of 2, speeding exceeding 30% of the regulated speed may get assigned a weightage of 7, and speeding exceeding 30% of the regulated speed with a child in the vehicle 10 may get assigned a weightage of 10.

[0034] The weightage may also be determined by the user to include more comprehensive factors. For example, the weightages can include a punishment system to penalize drivers who continuously committing the same risks. For example, the risk of not signaling when switching lane may 15 get assigned a weightage of 1. If the driver commits the same risk in a week, or any period of time set by the user, the same risk of not signaling when switching lane may get assigned an increased weightage of 2. The weightage can be user-defined to increase at a higher rate if the risk is being repeated over time, or to return to the initial value if the driver stops committing the risk 20 over a period of time (i.e., to reward drivers who correct their mistakes).

[0035] At step 508, a score is generated based on the respective weightages of the risks. The score can be calculated by summing the weightages of all the risks identified or other means of calculation defined by

the user. In the present example, a higher score indicates a higher driving risk.

[0036] The score can be related to a certain driver (e.g., for the use of insurance providers). For assign the risks occurred to the correct driver, available facial recognition methods can be employed on the image data of the camera with in-cabin view to identify the driver. Alternatively, facial recognition may be substituted with other biometric methods (e.g., fingerprint matching, iris matching) or identity documents (e.g., driver license, ID, passport, smart cards).

10 **[0037]** The score can be generated based on previous collected data within a predetermined period of time or can be generated for real-time data received from the vehicle. The data may be processed locally onboard by the computing device 10 located in the vehicle, or remotely in the cloud. Due to the extensiveness of the data, the user may obtain a wide range of information with the appropriate analysis methods additional to the driving risk. For example, studies based on the data can provide information on the drivers' response time, safest time of the day for driving, zones with high accident risks and the alike. Such information can be used for driving training (for both drivers and autonomous vehicles), accident preventing and onboard
20 intelligent driving system design purposes.

[0038] It should further be appreciated that the exemplary embodiments are only examples, and are not intended to limit the scope, applicability,

operation, or configuration of the invention in any way. Rather, the foregoing detailed description will provide those skilled in the art with a convenient road map for implementing an exemplary embodiment of the invention, it being understood that various changes may be made in the function and
5 arrangement of elements and method of operation described in an exemplary embodiment without departing from the scope of the invention as set forth in the appended claims.

CLAIMS

1. A computing device for evaluating driving risk, comprising:
an input circuit configured to receive data from a vehicle, the data comprising at least one of GPS data, acceleration data or image data; and
5 a processor configured to:
train a situation classification model based on the data received from the vehicle using machine learning methods to classify various driving situations,
wherein the processor is further configured to:
10 identify a plurality of risks based on the data received from the vehicle and one or more of the various driving situations classified by the situation classification model;
determine a plurality of weightages, wherein a respective weightage is assigned for each of the plurality of risks; and
15 generate a score based on the plurality of weightages for the plurality of risks.
2. The computing device of claim 1, wherein the image data comprises at least one of images of road condition, images of traffic condition, images of
20 weather condition, images of lighting condition or images of other vehicles.

3. The computing device of claim 1, wherein the image data comprises at least one of images of a driver's postures inside the vehicle or images of the driver's movements inside the vehicle.

5 4. The computing device of claim 3, wherein the processor is further configured to identify the driver of the vehicle based on the image data using facial recognition.

5. The computing device of claim 1, wherein the processor is further
10 configured to identify the driver of the vehicle using the driver's biometric data.

6. The computing device of claim 1, wherein the processor is further
configured to identify the driver of the vehicle using the driver's identity
15 document or data.

7. The computing device of claim 1, wherein the plurality of risks
comprises at least one of not keeping a safe distance, not following traffic
lights or traffic signs, not slowing down at road junctions, not signaling, not
20 doing safety checks or reckless driving.

8. The computing device of claim 1, wherein identifying the plurality of risks based on the data received from the vehicle is based on training on previous data received from vehicles using machine learning methods.
- 5 9. The computing device of claim 8, wherein machine learning methods comprises deep learning, random forest, support vector machines, linear regression, logistic regression, nearest neighbor and decision tree.
- 10 10. The computing device of claim 1, wherein the score is used for at least one of assessing the driver's behaviors, providing analysis data to insurance providers or predicting an accident of a semi-autonomous or autonomous vehicle.
- 15 11. The computing device of claim 1, wherein the processor is configured to generate the score based on a sum, wherein the sum is based on the respective weightage assigned for the each of the pluralities of the risks.
- 20 12. The computing device of claim 11, wherein the sum is based on a number of occurrences for the each of the pluralities of the risks and the respective weightage assigned for the each of the pluralities of the risks.
13. The computing device of claim 12, wherein the respective weightage assigned for the each of the plurality of risks increases at a predetermined

rate, wherein the predetermined rate is based on the number of occurrences for the respective risk in a predetermined period of time.

14. A method for evaluating driving risk, comprising:

5 receiving data from a vehicle, the data comprising at least one of GPS data, acceleration data and image data;

training a situation classification model based on the data received from the vehicle using machine learning methods to classify various driving situations;

10 thereafter identifying a plurality of risks based on the data received from the vehicle and one or more of the various driving situations classified by the situation classification model;

determining a plurality of weightages, wherein a respective weightage is assigned for each of the plurality of risks; and

15 generating a score based on the plurality of weightages for the plurality of risks.

15. The method of claim 14, wherein the image data comprises at least one of images of road condition, images of traffic condition, images of
20 weather condition, images of lighting condition or images of other vehicles.

16. The method of claim 14, wherein the image data comprises at least one of images of a driver's postures inside the vehicle or images of the driver's movements inside the vehicle.

5 17. The method of claim 16, wherein the method further comprises identifying the driver of the vehicle based on the image data using facial recognition.

18. The method of claim 14, wherein the method further comprises
10 identifying the driver of the vehicle using the driver's biometric data.

19. The method of claim 14, wherein the method further comprises identifying the driver of the vehicle using the driver's identity document or data.

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20. The method of claim 14, wherein the plurality of risks comprises at least one of not keeping a safe distance, not following traffic lights or traffic signs, not slowing down at road junctions, not signaling, not doing safety checks or reckless driving.

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21. The method of claim 14, wherein identifying the plurality of risks based on the data received from the vehicle is based on training on previous data received from vehicles using machine learning methods.

22. The method of claim 21, wherein machine learning methods comprises deep learning, random forest, support vector machines, linear regression, logistic regression, nearest neighbor and decision tree.

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23. The method of claim 14, wherein the score is used for at least one of assessing the driver's behaviors, providing analysis data to insurance providers or predicting an accident of a semi-autonomous or autonomous vehicle.

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24. The method of claim 14, wherein the method comprises generating the score based on a sum, wherein the sum is based on the respective weightage assigned for the each of the pluralities of the risks.

15 25. The method of claim 24, wherein the sum is based on a number of occurrences for the each of the pluralities of the risks and the respective weightage assigned for the each of the pluralities of the risks.

20 26. The method of claim 25, wherein the respective weightage assigned for the each of the plurality of risks increases at a predetermined rate, wherein the predetermined rate is based on the number of occurrences for the respective risk in a predetermined period of time.