

GripSense: A Sensor Fusion-Based Two-Tier Alcohol Detection and Safe Engine Control System: A Review

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Abstract — Drunk driving is a major cause of road accidents, and it can be prevented. Many low-cost alcohol detection systems use only one breath sensor and one fixed limit. If the reading goes above the limit, the engine is switched off. If not, the car keeps running. This paper looks at what IEEE research papers say about doing this in a better way. We studied 11 IEEE papers (8 journal papers and 3 conference papers). They cover face-based detection, sensor-based detection, engine lock systems that use the MQ-3 sensor, portable breath testers, wearable sensors, and skin conductance sensing while driving. The papers show that deep learning on face images can reach about 87 to 90 percent accuracy, that wearable sensors with machine learning can reach about 90 percent, and that cheap breath sensors can lock an engine and send the location of the vehicle. They also show some problems. Accuracy is lower for some groups of drivers. Even sober people breathe out a small amount of ethanol. Skin signals change with stress and not only with alcohol. And very few papers test what the vehicle should do after alcohol is found. Based on this, we describe GripSense. It is an idea for a system that puts a skin temperature sensor, a skin conductance (GSR) sensor and an MQ-3 breath sensor on the steering wheel and combines their readings. It reacts in two steps: a warning for a low level, and a slow, safe slowdown for a high level. GripSense is not built or tested in this paper. The paper gives a comparison of 11 studies, a proposed design, a list of research gaps and a plan for testing.

Keywords— Alcohol detection; Drunk driving prevention; Sensor fusion; MQ-3 gas sensor; Galvanic skin response; Skin temperature; Engine control; Anomaly detection; Internet of Things; GripSense.

I. INTRODUCTION

Drunk driving has been a road safety problem for a long time, and the way it is checked has not changed much. Police still mostly use breath testers. The driver has to blow into the device, and since many people use the same device, there are hygiene concerns [1]. Because of this, researchers are trying methods that do not need a separate test. Some use cameras that look at the driver's face [1]. Some use anomaly detection, which learns what normal sober behaviour looks like from sensor data [2]. Others combine image processing with a network of sensors [3]. There is also work on alcohol sensing for driver safety in intelligent transport systems [4].

At the low-cost end, many student and small-team prototypes use an MQ-3 alcohol sensor, a microcontroller and a relay. When alcohol is found, the engine is stopped and the location of the vehicle is sent to someone [5]. These prototypes show that the basic idea works. But they have some common problems. One cheap sensor has to make the whole decision. Sober people also breathe out a little ethanol, so the limit has to be chosen carefully [6]. And the reaction is usually all or nothing. If the engine is cut suddenly while the car is moving, that can be dangerous too.

This review is built around a project called GripSense. The idea is to put a skin temperature sensor and a galvanic skin response (GSR) sensor on the steering wheel, where the driver's hands rest. An MQ-3 breath sensor is added, and the three readings are combined. The system then reacts in two tiers. If the alcohol level is low, it only gives a warning and saves a log entry. If the level is high, it slows the vehicle down gradually and safely instead of switching the engine off at once. This paper has four aims. The first is to summarise what IEEE papers say about each sensing method. The second is to compare some of these studies. The third is to find the gaps between prototypes and systems that can really be trusted. The fourth is to suggest future research and a design for GripSense.

II. REVIEW METHODOLOGY AND LITERATURE SELECTION CRITERIA

1. How the papers were searched

This is a narrative review, not a full systematic review. The search was done in October 2026 using a general web search engine, and then the results were followed to IEEE Xplore records, DOI pages and author or college repositories. The search words included alcohol detection, drunk driving, MQ-3, engine lock, breath analysis, wearable biosensor, skin conductance, driver stress and driver drowsiness. We also

added the names of IEEE journals such as IEEE Access, IEEE Sensors Journal and IEEE Transactions on Intelligent Transportation Systems. We could not search IEEE Xplore, Scopus or Web of Science directly, so we do not report how many records were found at each step, and there is no PRISMA flow diagram. Some useful IEEE papers may have been missed. Anyone who continues this work should repeat the search directly in IEEE Xplore.

2. Selection criteria

Table 1: Inclusion and exclusion criteria

Criterion	Included	Excluded
Publisher	Papers published by IEEE. Journal papers were preferred. IEEE conference papers were used only when no suitable journal paper could be checked.	Non-IEEE papers, theses, patents, websites and company pages
Topic	Alcohol or drunk detection for drivers; MQ-3 or other breath gas sensing; skin, wearable and body signal sensing in drivers; anomaly detection and driver state monitoring	Studies on alcohol treatment that have nothing to do with sensing
Checking	Title, authors, journal, volume and pages confirmed from an IEEE record, a DOI, or a trusted reference list	Papers whose details could not be confirmed
Period	Older basic work and recent work up to 2026	Duplicate or replaced versions

3. What was selected

Eleven papers were selected. Eight are IEEE journal papers ([1] to [4], [7], [8], [10], [11]) and three are IEEE conference papers ([5], [6], [9]). We read the abstracts of [1], [2], [5], [6], [7] and [9]. For [3], [4], [8], [10] and [11], we could only check the record and the title. So these five papers are used only for their topic, and we do not say anything about their results. All numbers are given as the authors published them. We did not recalculate anything.

III. LITERATURE REVIEW

1. Detecting drunk drivers with cameras

Chang et al. built a deep neural network with two stages. The first stage uses a simplified VGG network to guess the age range of the person. The second stage uses a simplified

DenseNet to find facial features of drunk driving. The age stage was 86.36 percent accurate. Drunk driving recognition was 94, 83 and 81 percent accurate for the age groups 18 to 30, 31 to 50 and 51 and above. The whole system reached 89.62 and 87.44 percent [1]. This method needs no breath test, which solves the hygiene problem the authors mention. But it works worse for older drivers, so it may not be equally good for everyone.

2. Anomaly detection with sensor data

Dairi et al. treated drunk driving detection as an anomaly detection problem. Their method uses t-SNE to pull out features and an Isolation Forest to decide whether the driver is drunk [2]. The good thing about this idea is that it learns what is normal and flags anything different. This suits real life, where there is a lot of sober data and very little drunk data. Rosero-Montalvo et al. describe an embedded system that combines image processing with a sensor network to detect the drunk status of a driver [3]. Mehmood et al. work on alcohol sensing and driver safety enforcement in intelligent transport systems [4]. For these two papers, we could only check the titles, so we do not describe their results.

3. Low-cost breath sensor prototypes and engine lock

Pavan Kumar et al. made a microcontroller-based system where an MQ-3 sensor checks the breath of the driver and the passengers. If the driver is found drunk, the system stops the engine, sends an alarm to the transport owner and shares the live location with GPS. The authors say their tests confirmed correct detection, reliable engine stop and accurate location tracking [5]. The actual numbers were not in the abstract.

Wakana and Yamada looked more carefully at the breath itself. Their portable device has four sensors. One is a water vapour sensor that checks whether the gas is really human breath. The other three are semiconductor sensors for ethanol, acetaldehyde and hydrogen. The results go through a smartphone to a cloud system. They tested more than 30 devices in the field. Even people who had not taken any alcohol showed average levels of 1.8 ppm ethanol, 1.9 ppm acetaldehyde and 0.1 ppm hydrogen, because of the normal working of the body [6]. This teaches two things. A breath sensor should first check that it is really measuring breath. And a limit set at zero would wrongly flag sober drivers.

4. Body signals and wearable sensors

GripSense depends on skin signals, so it is important to know what IEEE papers say about them. Healey and Picard recorded ECG, muscle activity (EMG), skin conductance and breathing during 24 real drives, each at least 50 minutes long, on open roads. Using five-minute pieces of data, they separated three

levels of driver stress with more than 97 percent accuracy. They found that skin conductance and heart rate were the signals most closely linked with stress [7]. This result matters in two ways. It shows that skin conductance can be recorded inside a real car. But it also shows that skin conductance reacts strongly to stress, so any alcohol detector that uses it must be able to tell stress apart from drunkenness. Poh et al. describe a small wearable sensor that measures electrodermal activity for a long time without disturbing the user [8]. This supports the idea that skin sensing can be made small and comfortable.

Rumbut et al. used data from wearable sensors and supervised learning to detect intoxication from different substances. They combined two sets of offline data and classified about 90 percent of the samples correctly. Skin temperature and average body movement were the most useful signals. They also say that people, sensors, drugs and surroundings are all different, so it is hard to make one model that works everywhere [9]. This supports using skin temperature together with GSR. It also supports using each driver's own normal values as a baseline.

5. Other driver state monitoring

Alcohol is only one of the driver states that matter. Kaplan et al. wrote a survey on analysing driver behaviour for safe driving [10]. Yu et al. worked on detecting driver drowsiness [11]. We could only check the titles of both, so we cite them only for their topic. They are still useful here, because a sleepy driver and a drunk driver can look similar, and a real system may need to watch for more than one condition.

IV. COMPARATIVE ANALYSIS OF EXISTING STUDIES

Table 2 compares the 11 papers. The numbers are copied as published. They cannot be compared directly, because the tasks, the data and the testing methods are different. "Title only" means that only the record and title could be checked.

Table 2: Comparison of the reviewed IEEE studies

Study	Objective	Sensing / method	Reported findings	Limitations
Chang et al., 2021 [1]	Detect drunk driving from the face	Two-stage deep network (VGG, DenseNet)	89.62 % and 87.44 % overall; 94, 83 and 81 % by age group	Lower accuracy for older drivers; needs a camera
Dairi et al., 2022 [2]	Find the drunk status of drivers	t-SNE features with Isolation Forest (anomaly detection)	Method reported as effective	Numbers not captured here
Rosero-Montalvo et al., 2021 [3]	Detect drunk status of the driver	Embedded system with image processing and sensor network	Title only	Results not checked
Mehmood et al., 2022 [4]	Alcohol sensing for safety in transport systems	Alcohol sensing	Title only	Results not checked
Pavan Kumar et al., 2025 [5]	Engine lock with driver and passenger checks	MQ-3, microcontroller, GPS	Correct detection and reliable engine stop reported	Conference paper; numbers not captured; all-or-nothing reaction
Wakana & Yamada, 2019 [6]	Portable breath alcohol detection	Water vapour sensor plus ethanol, acetaldehyde and hydrogen sensors; cloud	Sober users showed 1.8, 1.9 and 0.1 ppm on average; more than 30 devices tested in the field	Conference paper; breath only; not inside a vehicle
Healey & Picard, 2005 [7]	Driver stress from body signals	ECG, EMG, skin conductance, breathing	Over 97 % for three stress levels; skin conductance and heart rate most linked	Measures stress, not alcohol; 24 drives

Study	Objective	Sensing / method	Reported findings	Limitations
Poh et al., 2010 [8]	Comfortable skin conductance sensing	Wearable EDA sensor	Title only	Not about alcohol
Rumbut et al., 2020 [9]	Detect substance use with wearables	Wearable sensors; supervised learning	About 90 % classified; skin temperature and movement most useful	People, sensors and surroundings differ; conference paper
Kaplan et al., 2015 [10]	Survey of driver behaviour analysis	Survey	Title only	General, not only alcohol
Yu et al., 2019 [11]	Detect driver drowsiness	Condition-adaptive representation learning	Title only	About drowsiness, not alcohol

Three things can be seen from the table. First, the cheapest systems are explained the least. The MQ-3 prototype reports a working demo but not enough details like number of people, conditions or how it was tested [5]. Second, the best accuracy figures come from camera and learned models [1], [2]. But these were tested on image or sensor data sets, not on a steering wheel sensor that combines breath with skin signals. Third, sensing and reaction are studied separately. The detection papers stop at saying drunk or not drunk. The engine lock paper

stops at blocking the engine [5]. In the papers we could check, nobody studied what a vehicle should do at each alcohol level.

V. RESEARCH CHALLENGES AND IDENTIFIED GAPS

Table 3 lists the gaps that the checked papers support, and the direction each one points to.

Table 3: Research gaps and directions

Gap	What the papers show	Direction
Contact breath tests and single sensors	Breath testers need contact and raise hygiene concerns [1]; prototypes depend on one MQ-3 and a fixed limit [5]	Use a sensor on the steering wheel that needs no extra test; combine several signals and report how sure the system is
Fixed limits on breath gases	Sober people breathe out small amounts of ethanol, acetaldehyde and hydrogen [6]	Set limits using data from sober drivers; check that the sensor is really sampling breath
Skin signals are not only about alcohol	Skin conductance and heart rate follow driver stress [7]; people, sensors and surroundings vary a lot [9]	Use each driver's own baseline; treat skin signals as extra support next to the breath reading
Accuracy not equal for all drivers	Face-based accuracy is lower for older drivers [1]	Test across ages and conditions and report results for each group
Anomaly detection not yet tried with steering wheel sensors	Anomaly detection looks promising for drunk status [2]	Learn each driver's sober baseline and flag changes; compare with other models
No tested step-by-step reaction	The engine lock prototype only blocks the engine [5]; the other papers stop at detection	Design and test slow, controlled braking with hazard lights and a safe stop rule
Testing in real vehicles	Body signals have been recorded on real drives [7], but the alcohol papers checked here are lab, image or prototype studies	Test the sensors in a parked car and a moving car, with a reference breath analyser

Gap	What the papers show	Direction
Human trials, privacy and misuse	Not covered in the checked papers	Follow ethics approval; make clear rules on how long data is kept and who is informed

Two of these points need a little more explanation. The first is false alarms. If a system blocks sober drivers, people will turn it off or ignore it. So the cost of a false alarm must be balanced against the cost of a miss. This is one reason why GripSense has two tiers with different limits. The second is the reaction itself. Cutting engine power at speed removes engine braking, and in some vehicles it may also reduce power steering or brake assist. So a real system must work with the vehicle's own control system and be tested for safety. A bench prototype cannot prove this.

VI. PROPOSED RESEARCH DIRECTIONS

1. GripSense design idea

Figure 1 shows the proposed GripSense design. It is based on the gaps above. It is only an idea. It has not been built, tested or validated, and we do not claim any performance figures. The solid arrows show the normal flow of data. The dashed arrow shows an offline loop, where limits or models are updated only after they are tested again.

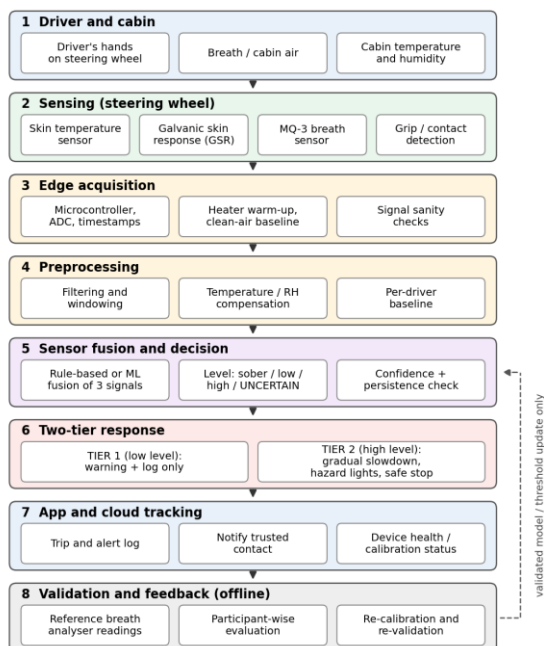


Fig. 1. Proposed GripSense design (conceptual, not tested).

Sensing

The skin temperature and GSR sensors are placed on the steering wheel, where the hands rest. Skin conductance has already been recorded in real driving [7], and small comfortable sensors exist [8]. A contact sensor checks that the driver is really holding the wheel. An MQ-3 sensor samples the air near the driver. Following [6], the breath channel also has a humidity or water vapour reading, so the system can tell when it is sampling real breath. A cabin temperature and humidity sensor is used as a reference. We have not fixed the exact sensor models.

Edge processing

A microcontroller takes care of heater warm-up, a clean-air baseline, time stamps and basic checks. It ignores readings taken when the hands are not on the wheel. After that come filtering, cutting the signal into windows, and correction for temperature and humidity. For the skin signals, each driver's own sober values are used as a baseline. This is because people differ a lot [9], and because skin conductance also changes with stress [7].

Fusion

The first prototype can use simple rules. For example, the level is raised only if the breath signal and at least one skin signal agree. Later, an anomaly detector like the one in [2] can be compared with the rules on the same data, since it only needs to learn the driver's normal state. The output is a level (sober, low or high) with a confidence value. There is also an "uncertain" state, and this state never triggers the engine reaction.

2. Two-tier reaction

The main idea in GripSense is that the reaction should match the level. In Tier 1, if a low level continues for several readings in a row, the system warns the driver and saves a log entry. Nothing else happens. In Tier 2, if a high level continues and other signals support it, the reaction depends on the state of the vehicle. Before the trip, the vehicle is not allowed to start. During the trip, the system gives a sound and light warning, switches on the hazard lights, reduces the speed slowly, and brings the vehicle to a stop only when it is safe. The engine is not cut suddenly. A trusted person can be informed through an app with the location of the vehicle, like in [5]. The limits, the

waiting time and the braking profile have to be decided from test data. This paper does not claim any fixed values.

3. Evaluation plan

The testing should avoid the weak points found in Section 5. The data should be split by person and by session, and at least one test should use data collected later than the training data. In this way, almost identical readings from the same person never appear in both training and testing. The main measures are the miss rate at Tier 2, the false alarm rate at both tiers, the delay in detection, and what happens when the grip is lost or the cabin is hot, humid or has been cleaned with an alcohol sanitiser. Results should be given for each group of people, as [1] does for age. Every reading should be compared with a reference breath analyser. A sensible order is to first test the MQ-3 in a controlled ethanol vapour setup, then test the skin sensors on sober volunteers in different conditions including stress, and only after that think about trials where people drink alcohol. Those trials need approval from an ethics committee, medical supervision and informed consent.

4. Near, medium and long term

In the near term, the sensing and edge parts can be built on a bench or a small test platform. Sober baseline data can be collected under different temperature, humidity, stress and grip conditions, and rule-based fusion can be compared with an anomaly detector. In the medium term, ethics-approved trials can be done with a reference breath analyser, and the Tier 2 slowdown can be tested on a controlled track or a scaled model. In the long term, GripSense can be connected to the control system of a real vehicle and tested across seasons, drivers and cabin conditions. Driver acceptance, privacy and misuse should also be studied. Combining GripSense with camera methods like [1] and drowsiness monitoring like [11] is another option.

VII. CONCLUSION AND FUTURE SCOPE

The IEEE papers we could check show that alcohol detection in vehicles can be done in several ways. These include learned image models, anomaly detection on sensor data, cheap MQ-3 breath prototypes that lock the engine, and body signal sensing that works in real driving. They also show why low-cost systems cannot yet be trusted. They use a single sensor with a fixed limit. Accuracy changes from one group of drivers to another. Skin signals react to stress as well as alcohol. And the reaction is all or nothing, which has not been studied for safety. GripSense is suggested as one answer to these gaps. It combines skin temperature and GSR from the steering wheel with an MQ-3 breath sensor, uses each driver's own baseline, says openly when it is unsure, and links the reaction of the

vehicle to the alcohol level. The aim is a system that is cheap, personal to the driver and safer in how it reacts. These are design ideas and not results. The next steps are to build the sensing and edge parts, collect carefully labelled data, test by person and over time, and test the step-by-step slowdown in controlled conditions. In future, more IEEE journal papers on MQ-3 systems, skin conductance sensing and safe stop control should be added by searching IEEE Xplore directly.

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