THE POTENTIAL FOR ADAPTIVE SAFETY THROUGH IN-VEHICLE BIOMEDICAL AND BIOMETRIC MONITORING

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ABSTRACT

A 2009 study by the National Highway Traffic Safety Administration identified certain medical conditions as contributing factors in crash causation (Hanna 2009). It was found that about 1.3% of all crashes included in the National Motor Vehicle Crash Causation Survey (NMVCCS) were precipitated by driver reported medical emergencies and 84% of the drivers in crashes precipitated by medical emergencies experienced seizures (epileptic and others), blackouts (non-diabetic), and diabetic reaction prior to the crashes. Drivers who had crashes precipitated by medical emergencies were more likely to sustain severe injury (28% for incapacitating injury and death for crashes with medical emergency; 11% for crashes without medical emergency). Thus, the premise exists that there may be benefit to identify the driver (and other occupants) of the vehicle as well as monitor their current health status through passive or active methods. This monitoring could take into account chronic conditions (such as bone mineral density) through driver input or through initial vehicle startup measurements which could be used to provide optimal comfort or safety system performance. Additional information about the driver's health or behavioral conditions could be interpreted from blood pressure, heart and respiration rate, blood glucose levels and other physiological parameters and could lead to vehicle intervention in driving and/or alert EMS or police of the impending health condition that may affect driving or cause a crash. This monitoring could be done in many ways such as the recent rapid growth in wearable technology with the ability to pair to apps.

This paper will discuss issues related to driver behavioral and health monitoring and review potential technologies for monitoring and as well as methods for biometric identification. Recent publications on driver crash risk due to chronic and acute health conditions will be summarized. Finally, applications that may be associated with the monitoring will be discussed.

INTRODUCTION

Driver state is an important factor affecting safe driving behavior. Detection and intervention of drowsiness, distraction and drunkenness have been studied by many up to now. The decline of an individual driver’s health is another potential cause for a significant proportion of crashes. Researchers as early as 1967 recognized medical impairment as a possible contributor to traffic “accidents” (Waller, 1967). In his report, Waller outlined seven criteria that should be adhered to in a study of this subject, including “there must be a reasonable mechanism for identifying most of the high risk persons, and for doing so early enough to avoid a substantial portion of their accident experience”. In a recently released report, the National Highway Traffic Safety Administration reviewed crashes from the National Motor Vehicle Crash Causation Survey (NMVCCS) to determine the “critical reason, which is the last event in the crash causal chain, and concluded that driver was that reason for 94% of crashes in that nationally represented survey (NHTSA, 2015). Of those 94% of crashes (representing over 2 million crashes), seven percent, or 145,000 crashes were attributed to a driver “non-performance error”, which could be drowsiness or an acute medical condition. Using the same data set, Hanna (2009) found that 1.3% of all crashes involving light passenger vehicles in NMVCCS were precipitated by a driver's medical emergency and 84% of the drivers in crashes precipitated by medical emergencies had experienced seizures (related to epilepsy and other conditions), blackouts (non-diabetic), and diabetic reaction prior to the crashes (Figure 1). Hanna found that the drivers who had crashes precipitated by medical emergencies were more likely to be more severely injured (i.e. 28% suffered incapacitating injury and death in crashes with a medical emergency compared to 11% in crashes without medical
emergency). Although the ratio of the crashes related to acute medical emergencies was small in the study, there were many other disease-related cognitive and psychomotor impairments (chronic) that may have increased the risk of crash. The Federal Motor Carrier Safety Administration (FMCSA) commissioned a series of studies to determine risk of motor vehicle crash for a variety of medical disorders based on reports and medical expert panel opinions provided by (Table 1, FMCSA, 2007-2011). The table shows a statistically significant increased risk for a crash based on a driver having one of several disorders. Obstructive sleep apnea (OSA) is shown to have the highest relative risk (1.30-5.72). Another general consideration is that some diseases such as type II diabetes, cardiovascular disease, mild cognitive impairment (MCI) and Alzheimer’s disease are associated with aging. Now that the aging population is growing rapidly in the US, crash rates of occupants with those diseases may see increases despite the recent report by the Insurance Institute for Highway Safety (IIHS) indicating that fatal crash involvement rates of older drivers were decreasing faster than those of younger drivers (IIHS Status Report, 2014). NHTSA’s 5-year plan for traffic safety for older people (NHTSA, 2013) also highlights older drivers’ risk in association with increased medical problems.

Advances in vehicle electronics have made it possible for drivers and passengers to customize their driving experience in many ways. Personalized settings for seat position, as well as heating/cooling/ventilation and entertainment (separated for drivers and passengers) have been available for many years. Recent technological progress in diversity, sensitivity, data capacity and miniaturization of biometric and biomedical instrumentation sensors and devices are enabling the general public to have more real-time access to personal health status as well as enjoy more security for their personal electronic devices. Recent development has resulted in devices that can be embedded anywhere such as clothes, wristbands, watches, vehicle interiors, etc. to detect and report medical information such as body temperature, heart, respiration and perspiration rates, blood glucose and oxygenation levels, and other physiological functions. This data combined with user identification through recognition of fingerprints, iris, facial and/or voice inputs can provide a rapid analysis of a person’s state of health. The availability and use of this information has implications in many markets and significant potential to increase driving comfort and safety when embedded into appropriate algorithms related to vehicle design and performance. For example, a vehicle that senses that the driver has an elevated body temperature and has increased his/her respiration rate significantly may automatically open windows or increase interior ventilation to improve comfort. Also, providing input to the vehicle that the driver is 75 years old and thus has reduced bone mineral density, the vehicle may adjust restraint system parameters to optimize occupant protection in the event of a crash. The same vehicle system could also forward the driver’s vital information to first responders and other health professionals even before they reached the scene of the crash.

![Figure 1. Type of medical conditions which precipitated crashes (Hanna, 2009).](image)

This paper will present the current state of passive personal identification and monitoring of a person’s health status, as well as the expected developments of such systems in the future. A discussion of how these devices could influence vehicle comfort and safety will be provided through a summary of the technology available or in development, the challenges of integrating the devices to the vehicle, the potential use, accuracy, standardization and privacy of data as well as other policy implications of this technology. Practical examples will be given to exemplify
the market readiness of technology and the potential for diversification of products and applications and their breadth and depth.

HEALTH CONDITIONS THAT MAY AFFECT DRIVING

Medical conditions are generally divided into two categories, chronic and acute problems. Some diseases have either chronic or acute problems and some have both. Effective in-vehicle interventions for these two aspects are different. The driver is at extremely high risk of crash in the case of acute health decline which shows distinctive physiological and behavioral changes. An in-vehicle system that detects a decline and controls the vehicle for an unresponsive driver may help to avoid a crash. On the other hand, chronic health problems develop slowly and degrade cognitive and behavioral performance of the driver over time, resulting in higher general risk of crash. In-vehicle systems that increase the safety margin of the vehicle based on individual’s driving ability may minimize the increased risk. The following discussion describes medical conditions that may affect driving.

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<thead>
<tr>
<th>Medical Condition</th>
<th>Relative Risk (95% Confidence Interval)</th>
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<tr>
<td>Cardiovascular Disease</td>
<td>1.43 (1.11-1.84)</td>
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<td>Diabetes Mellitus</td>
<td>1.28 (1.12-1.47)</td>
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<tr>
<td>Obstructive Sleep Apnea</td>
<td>1.30-5.72 (pooled studies)</td>
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<td>Seizure Disorders</td>
<td>1.13-2.16 (pooled studies)</td>
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<tr>
<td>Traumatic Brain Injury</td>
<td>1.32 (0.77-2.25)</td>
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Diabetes

The likelihood that a person has diabetes (type II) increases with age. Wild et al., (2004) estimated that the number of people over 65 years old with diabetes in developed countries will increase by 80% between 2000-2030 and the total number of people over the age of 46 with diabetes will be nearly 80 million people by 2030. An acute risk factor for driving is hypoglycemia (it can lead to coma) which can be caused mainly by insulin-dependent Type 1 diabetes, whereas the chronic risk factors for driving are neuropathy (decreased sensation at feet and hands), retinopathy (vision loss), and encephalopathy (cognitive decline), all of which can be caused by both Type 1 and Type II diabetes (Rizzo, 2011). However, scientific evidence for drivers with diabetes being at greater risk for crashes is not conclusive. Tregear et al. (2007) reviewed and conducted meta-analysis of thirteen studies, comparing crash risk among drivers with diabetes to drivers without diabetes, and found that the risk for crash among drivers with diabetes was 19% greater than the risk among drivers without diabetes (within the range published by FMCSA in Table 1). On the other hand, Tregear et al. found no statistically significant evidence to suggest that insulin-treated individuals are at higher risk for crash than individuals with diabetes not being treated with insulin. It seems that diabetes increases the crash risk but contributions from the acute symptoms and the chronic symptoms to the increased risk are not yet known. The American Diabetes Association (ADA) states that diabetes management and education of both patients and health care professionals is the important intervention to the driving risk due to hypoglycemia (American Diabetes Association, 2012).

Obstructive sleep apnea (OSA)

There is strong evidence that the highest relative risk of motor vehicle crash is for OSA, ranging between 1.30 and 5.72 (FMCSA, 2007, Table 1). There is evidence that OSA affects a significant portion of the population regardless of whether it is diagnosed or undiagnosed. Hiestand et al. (2006) conducted a telephone interview of 1506 US adults using the Berlin questionnaire and found that 26% of respondents met the criteria indicating a high risk of OSA. NHTSA estimated that 1.4% of total crashes and 1.75% of fatal crashes were related to sleepiness (NHTSA, 1985). However, Leger (1994) suggested that NHTSA’s estimation was underestimated and provided a new estimation of sleep-related crash rates as 41.6% of total crashes and 36.1% of fatal crashes. Because of potential under-reporting and inability to determine post-mortem that drowsiness or micro-sleep episodes contributed to the crash, there is no clear-cut estimation of crash rate related to OSA. However, considering the high risk factors which were estimated
in strictly controlled driving simulator studies, OSA should be one of the conditions that can contribute to a risk of a vehicle crash.

Another important aspect of OSA is the fact that the disease remains undiagnosed in many individuals. Hiestand et al. (2006) concluded that the prevalence of OSA in the US was estimated to be between 5% and 10%, but only 1 in 10 of those with OSA were adequately diagnosed and screened for Continuous Positive Airway Pressure (CPAP) treatment. Untreated OSA can cause daytime somnolence, cognitive impairment, loss in work productivity with a typical symptom of microsleep and increase risk of motor vehicle crashes. It should be also noted that some sleepy drivers are not aware of their impaired status, possibly because of related cognitive impairment of an altered frame of reference for fatigue (Rizzo, 2011).

Effects of OSA on driving performance have been investigated in driving simulator experiments by some researchers. It was found by Paul at al. (2005) and Boyle et al. (2008) that untreated OSA patients showed greater variation in steering, lane position and TLC (Time-to-Lane-Crossing) during micro-sleep episodes, and degree of driving performance decrement was correlated with microsleep duration, particularly on curved roads. Risser and Ware (1999) found that untreated OSA patients demonstrated increased lane position variability and road departure incident which were positively correlated with frequency and duration of attention lapses (sleeps). Drowsy driver detection and alert systems are commercially available now. However, it remains unknown to what extent the current technology detects the critical state of drivers with OSA featured by frequent occurrence of micro-sleep episodes and to what extent the technology can mitigate the risk of crash.

Other Disease Conditions

In addition to insulin dependent diabetes (typically Type I) and OSA, other diseases such as cardiovascular disease, seizure disorders and traumatic brain injury can also expose the driver to an increased crash risk due to acute symptoms (e.g.: heart attack and stroke, epileptic seizure). With cardiovascular disease, there are increasingly more middle-age and older drivers being treated for symptoms associated with atrial fibrillation and congestive heart failure. Also, conditions associated with respiratory health such as Chronic Obstructive Pulmonary Disease and asthma are becoming increasingly common in the adult population. These conditions can turn from chronic to acute without warning. Each acute health decline is associated with distinctive physiological and behavioral changes from the normal condition and it is important to have the ability to detect such declines of the occupant while in the vehicle to activate an in-vehicle intervention.

More long-term degenerative conditions include osteoporosis and mild-to-severe cognitive degeneration such as Alzheimer’s disease. Ridella et al. (2012) found that osteoporosis or poor bone quality was the most significant contributing factor to injury, specifically, incidence of rib fractures, in older occupants involved in an injury-producing car crash. These crashes typically involved lower crash speeds than did crashes involving younger injured drivers and occupants. While treatable with many medications, bone quality continues to diminish with age with evidence that the pace of bone loss is more significant in women than men. Cognitive impairments are more difficult to determine in real-time without an adequate baseline or history for comparison.

REVIEW OF CURRENT TECHNOLOGIES USING DRIVER MONITORING

Occupant Identification

A first step in the process of monitoring is passive, non-invasive identification of the driver and perhaps passengers. The driver’s identification would be useful in a host of different applications. Establishing identity may allow for the vehicle to create a baseline of the occupant’s health status that can be used in current as well as future driving tasks. Algorithms may be developed for the vehicle to learn how it is driven in certain situations and the associated physiological measurements specific to that person. Also, there may be situations where several drivers share a single vehicle such as the use of a family car, where there may be a range of driving abilities. A teenager who is enrolled in a graduated licensing program may have certain vehicle restrictions put upon them whereas other members of the family may enjoy the full privileges of driving. Therefore, based on the driver’s identity, a monitoring system would adjust the vehicle’s abilities or monitor highly complex driving tasks more closely.
In addition, a history of the driver’s performance would also lend insight into the longitudinal data for comparative purposes. This information could be used to determine long-standing trends in performance such as declining mental capacities (e.g. Alzheimer’s or dementia), health issues, changes in driving performance, etc.

Technology to determine identity has grown exponentially in the past few years due to consumer demand for greater security of data. Much of this technology has the ability to be adapted to the vehicle environment or brought in through portable devices. Camera-based technology can be used for identification through facial recognition or iris analysis software. Fingerprint, vascular pattern and voice-recognition scanning are other methods of uniquely identifying an individual. An alternative to passive identification is the driver’s user provided information through a key card, implantable radiofrequency ID or RFID or other device that uniquely identifies an individual.

**Behavioral Monitoring (DrIIVE)**

Driver Monitoring of Impairments and Inattention using Vehicle Equipment (DrIIVE) is a current NHTSA project that uses driver monitoring data. DrIIVE is focused on the development of an algorithm that can accurately identify and distinguish among different forms of inattention or impaired driving including alcohol-impaired, drowsy, and distracted driving. DrIIVE determines driver behavior data from vehicle measures such as steering and pedal inputs, lane variability, and compares signatures of normal driving with impaired driving. The goal is to use the DrIIVE algorithm to identify and evaluate the effectiveness of driver monitoring countermeasures on impaired driving behavior.

**Alcohol Impairment (DADDS)**

In 2008, NHTSA launched a cooperation program to develop in-vehicle technology that could accurately, precisely, and reliably measure a driver’s blood alcohol concentration. in a non-invasive way in a very short time. (Monk, 2012). Now in it’s second phase, two subsystems have been developed and are being integrated into a research vehicle for further testing. One system is breath based and continually samples the area around the driver for alcohol and carbon dioxide through an infra-red sensor whose measurements can be converted into a blood alcohol concentration. A second subsystem is touch-based and can measure the absorbed near infra-red light in a person’s finger and derive an alcohol concentration. These systems have the dramatic potential to reduce crashes and fatalities involving drunk drivers by denying the driver the ability to start and drive the vehicle.

**Physiology/Health Monitoring**

Monitoring driver health should be non-invasive and passive. Both in-vehicle and wearable technology have been developed, however, only wearable technology has been commercialized to date. As sensor technology has become smaller and less expensive, a vast array of sensor applications have been developed or published. Ford Motor Company, working with a restraint and sensor supplier, developed a prototype vehicle to measure a variety of physiological signals (Watson et al, 2011). Figure 2 below indicates that they were looking at both comfort (temperature difference) and real-time physiology (heart and respiration rate). They indicated that the signals could be integrated for use in assessing driver performance as a function of wellness, workload, and stress. Ford also has demonstrated an in-vehicle glucose monitoring system that could detect a driver’s possibility for a diabetic episode (Ford, 2011).

Demonstrations of blood oxygenation measurements using a variant of typical finger-tip pulse oximeters, Meditech 2011), blood pressure and bone mineral density bring more information about driver/occupant health into the vehicle. The BOSCOS (BoneSCanning for Occupant Safety, Hardy et al, 2005) project created an in-dashboard ultrasound sensor that could deduce bone strength based on measurements taken from the distal third of a finger when inserted into the device.

Wearable devices or mobile human health monitoring is a maturing area of health awareness particularly in the sports medicine market. Miniaturized electronics or MEMS technology has allowed for creation of wearable wrist bands, head bands, even undergarments that are capable of accurately measuring heart rate, respiration, sweat production, etc. These devices are usually coupled to a portable electronic device application to record daily exercise results and associated physiological responses. The applications have algorithms to detect medical issues and
performance progress with the person wearing the technology as well as determine stress or anxiety levels. The cost of these devices has dropped dramatically in the past several years with many devices selling in the $50-$150 range. The sophistication, accuracy and reliability of these devices is steadily improving such that some diagnosis of heart and respiratory health may be deduced from the signals rather than just the instantaneous rates that are reported by the devices.

Figure 2. Examples of prototype health monitoring sensors embedded in vehicle components (Wired, 2011)

Establishing a Baseline

Another new challenge within the scope is connection and integration of monitoring the state of the driver in the home (off board) and in the vehicle (on board). Monitoring a person’s life in the home through so called “Smart Home” or “Wearable sensors” is becoming important for “Aging in Place” or “Tailor-made Health Care” and it is actively being tested by research projects for its effectiveness and clarification of system and social requirements. However, there are no systems / research projects focusing on integration of on and off board driver monitoring. Early signs of an acute health problem may be detected in the home before driving and such data can be brought into the vehicle to provide the in-vehicle monitoring system with an initial parameter set to raise the sensitivity of detection. For example, lower glucose level data or poor sleep quality data measured in the home may be used in the vehicle for earlier detection of hypoglycemia and frequent micro-sleep occurrence (Table 2). Driver state monitored in the home and in the vehicle can also make use of cause-effect relationships. For example, failure to take medicines in the home may increase the possibility of occurrence of hypoglycemic episodes or epileptic seizure behind the wheel. Such behavioral data measured in the home can also be brought into the vehicle to enhance or change the in-vehicle intervention strategy (e.g. failure to take anti-seizure medicine locks the ignition). Integration of on- and off-board driver monitoring will increase accuracy of detection of drivers’ health problems and strengthen the intervention strategy to avoid crash.

Another example of driving performance data being brought into the off-board network involves continuous monitoring of the driving environment. Driving includes many complex and parallel cognitive and physical tasks under certain levels of stress that may magnify certain aspects of a driver’s chronic health problems (e.g. cardiovascular diseases). Therefore, a driver’s state measured in the vehicle can be brought into a hospital or a smart home to be integrated with other behavioral and physiological data measured in the home to diagnose the chronic health state with better accuracy or in an earlier phase.
IMPLEMENTATION/APPLICATION

Evolution of the current driver state monitoring technology and integration with vehicle-embedded biometric sensors or wearable sensors with wireless connection to the vehicle (on-board monitoring) should be able to detect some or all of the acute health declines in real time. Candidates for on-board biometric sensors for each of the driver’s acute health decline are summarized in Table 2. Most of the biometric sensors for on-board monitoring shown in Table 2 are still under research or development. Applicability of these sensors to the detection of acute symptoms needs to be investigated with consideration for the cost and the user acceptance.

If the driver-state monitoring can detect early signs of a decline while the driver is still conscious, a multilayered intervention strategy using information and assistive vehicle control could be taken. When the driver fails to take actions to avoid a crash or if the system fails to detect early signs of the decline due to too rapid decline, future autonomous vehicle technology will be the key to avoiding crashes by bringing the vehicle safely to a stop on the hard shoulder of the road for the driver who is likely to be unconscious (i.e. Autonomous Emergency Stop System or AESS, Shunk, 2009, Nissan, 2013). Stopping a vehicle in busy traffic or high speed traffic could induce additional crashes involving other vehicles. Vehicle-to-vehicle communication to broadcast the emergency signal to surrounding and following vehicles could be included in the AESS. Accuracy of detection also needs to be high. Integration of environmental sensors with driver-state monitoring could be considered so that the system activates the Autonomous Emergency Stop System when the driver is in a health decline and the risk of crash is imminent (Figure 3).

The contributing factors and co-morbidities associated with the most common injuries also point to interventions that could benefit the older occupant. While knowing age of a driver or occupant may help in some driving task assistance, it is less of an indicator of overall health. Sensing occupant bone quality can lead to real-time adaptive restraint systems that lower the loads on the poorer quality bones of older or less healthy occupants and could help reduce incidence of rib injuries. Newer technologies such as 4-point belt systems and inflatable seat belts also help to reduce or distribute chest loading (Ridella, 2012).

Driver-state data measured in the vehicle can be also brought out of the vehicle to the off-board network. Advanced Automatic Collision Notification System (AACN) is an example that automatically sends notification of a collision event together with vehicle and driver-state data from the pre-crash phase to a hospital so that the ER will have sufficient preparation time prior to arrival of the casualties.

![Figure 3. Functional flow of Autonomous Emergency Stop System.](Image)
ISSUES

Privacy, protection and malicious intent

Since the devices and other instrumentation in the vehicle or on the occupant are measuring, monitoring, transmitting, and/or recording health status information, concerns arise regarding the protection and privacy of this data. The Health Insurance Portability and Accountability Act of 1996 (HIPAA) sets rights for an individual’s health information and prescribes rules and limits over who can review and receive that information. This rule applies to any form of the information whether it is oral, written or electronic. The information that is envisioned to be collected may not necessarily be covered by HIPAA depending on how it is collected and used. For example, it may be that the data is only used in a non-identifiable, real-time manner to inform the vehicle that the occupant is drowsy or has an abnormal condition. In other cases, when linked to driver/occupant identification technology, the data is personal and possibly subject to HIPAA. It could also be recorded and/or transmitted depending on application if there is a need to interpret the data in real-time by a health professional or to review the data by law enforcement at a later date should an event occur. HIPAA rules are very specific about cases such as this, however, it is likely an interpretation of HIPAA in the vehicle environment may need further review as this technology develops.

Another consideration is the malicious use of the health information data. Security of the data, whether stored in the vehicle, in a portable device or other form needs to be protected from other sources that could use or manipulate the data in harmful ways. For example, a baseline health information data set could be altered either through direct intervention or electronic methods such that an abnormal event would not be detected by the vehicle or software. An intervention or denial of service could occur during driving, thus making the system inoperative. There are endless scenarios that could occur depending on sophistication of the system. Current cybersecurity research regarding other vehicle communications should include the possibility of how the health and driver monitoring activities can be protected from mischievous intent.

Performance

Performance of such a system would require extensive testing for reliability, repeatability and reproducibility. In his short article nearly fifty years ago, one of Waller’s criteria for monitoring for physical impairment was that “few persons of low accident risk should be falsely categorized in the high accident risk group”. That is, the number of false-positive identifications should be minimized and conversely, the number of true-positives should be maximized. It is imperative that these devices are calibrated properly or can be re-calibrated based on manual feedback from the driver/occupant or perhaps periodically from a software “push” through an application or other connected technology whether portable or vehicle-based.

Cancelable

Finally, the driver and/or other occupants may reserve the right to cancel or not participate in real-time identification and monitoring. This may apply when a vehicle is not driven by an owner or designated driver for whom baseline data exists. Also, rental cars may either not be equipped with such devices or a driver may opt out from participation.

SUMMARY

The paper discussed the premise that identification of a vehicle driver (and/or occupants) as well as monitoring their health, mood or behavioral status while driving, may have significant value for safety. It is documented that health conditions may contribute to increased crash risk and that those with conditions have poorer outcomes should a crash occur. By monitoring a driver’s health status in real time, possibly comparing to a baseline value, acute conditions may be detected and a warning, intervention, or other countermeasure may be applied. There is abundant technology in development as evidenced by manufacturers’ documented research. Also, both traditional and non-traditional automotive suppliers have been involved in the early vehicle-based technology research, however, the sports market has dominated the wearable monitoring device development and production. Research projects in driver behavior, alcohol detection and a host of other technologies in development may lead to new advances in safety as the population of driver’s age and people are more aware of their own health status.
REFERENCES


<table>
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<tr>
<th>Monitoring modalities and sensors</th>
<th>Drowsiness/ Distraction</th>
<th>Drunkeness</th>
<th>Acute health problems</th>
<th>Other driver states</th>
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<td><strong>On-board monitoring</strong></td>
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<td>Wearable sensors</td>
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Table 2. Monitoring technologies and application to driver’s state.