Model-based approach for the estimation of drivers' mental workload with involuntary reflex eye movement

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Abstract

Traffic accidents, a key point in transportation, taking around 1.2 million lives every year, reducing 3% of gross domestic product, become a big problem in over the world, especially in developing country where the people try to become more advanced economically and socially (World Health Organization). According to United State National Highway Traffic Safety Administration (2010), human error accounts for 94% of traffic accidents, it means that the drivers can prevent the crash by avoiding dangerous behavior especially driver distraction that include visual, manual and cognitive demands.

On the other hand, in the aspect of technology, with the development in bioengineering, the advanced driver assistance system (ADAS) has been proposed to help the driver in the driving process for safety and better driving. By using input from multiple data sources include imaging, LiDAR, radar, and so on, the ADAS system can automate lighting, provide adaptive cruise control, incorporate GPS/ traffic warnings, connect to smartphones, automate braking, alert driver, show the blind spots, and so on. The technology makes it possible to create a new ADAS system which can reduce the number of accidents by alerting or turning on automating braking system when it can capture the driver distraction.

There are several previously studies relating to evaluate driver distraction, especially in the real time, which is the first step for creating ADAS system. In sum, the methodology for indicating driver distraction can be categorized into three groups: subjective measures, performance-based measures, and physiological measures. However, in the driving condition with visual stimulus and vibration from the vehicle, the most potential method is used physiological measure especially eye movement. Moreover, because of the low accuracy, up until now, the method using eye movement to indicate the driver distraction in the real situation has not been established.

A central goal of this thesis is to improve the methodology to detect driver distraction by using eye movement. To do that, there are several ways that proposed in the previous such as pupil diameter, saccades, or other. By considering the driving conditions, in this study, we applied the most possible method to update to detect

drivers' mental workload that use the difference between simulated eye movement by vestibulo-ocular reflex model plus optokinetic model and measurement one.

This research begins by briefly summarizing the analysis of driver accident and the main cause of traffic crash in **Chapter 1**. In addition, new technology in transportation is discussed, especially the advance driver assistance systems. Based on that, the importance of capturing driver cognitive distraction is pointed out. This chapter also presents the problem statement, objective, and the research outline for clearer understanding of our proposal. And then, in **Chapter 2**, the eye autonomy and the application of eye movement in transportation situation are briefly described.

In order for better understanding about mental workload, in **Chapter 3** gives a deep review of vestibulo-ocular reflex (VOR) model, optokinetic response (OKR) model, final common path, as well as detection of driver distraction. Taken Chapter 1, Chapter 2, and Chapter 3 together, the previous research suggests that the drivers' mental workload can be evaluated by monitoring eye and head movement. By considering the advantage and disadvantage of each method in case of driving, the eye simulation model proposed by Merfeld and Zupan is selected to increase the accuracy for simulating eye movement in natural situations.

In Chapter 4, with the main aims to introduce a novel methodology of developing the parameter identification for vestibulo-ocular reflex model, the review of genetic algorithm (GA) method and how to optimize the results of it are discussed. One interesting finding by using secondary data, the results of GA method show better performance than previous one. In addition, the results from 12 participants clearly support the hypothesis by improving the parameter identification method, the eye can possible to simulate even with changing gaze.

To simulate the eye movement in the realistic traffic environment, the combination of the VOR and OKR is presented in **Chapter 5**. Within this chapter, the effect of visual stimulus on eye movement during driving is investigated by examining two cases: driving with/without visual stimulus by means of a driving simulator. By comparing the observed eye movement and the simulation, the results indicate that after consisting of both VOR and OKR model, the eye movement is more accurate than VOR model only even in a naturalistic situation with optic flow of the visual scene.

Taken the new parameter identification method and consisting of both VOR and OKR models together, In **Chapter 6**, the relationship between eye movement and driver distraction with a driver simulator is explored. Within this chapter, three types of experiment are made: 1) evaluate driver distraction with changing gaze, 2) evaluate driver distraction with a stimulating environment, and 3) explore the different of eye performance under mental workload between young and old group. The results of analysis confirm the relationship between eye movement and driver distractions. Furthermore, the effect of mental workload and aging on driver distraction is analyzed. The results indicate that the older group shows worse performance compared with a younger group, especially under the distracted driving condition.

Chapter 7 presents a validation of the hypothesis in actual situations. The experiment in the real vehicle is conducted in two cases: 1) evaluation driver distraction for the participant in the passenger seat and 2) evaluate driver distraction for the driver who control the actual vehicle. This results clearly support the hypothesis that our method can be applicable for evaluating driver cognitive distraction not only in a driving simulator but also in actual vehicles.

Finally, **Chapter 8** summarizes research conclusions and provides some recommendations for future work. This work successfully to increase the accuracy of eye movement simulation by using vestibule-ocular reflex model. Furthermore, by consisting vestibule-ocular reflex model with optokinetic response model, the eye movement can be simulated with good matching even in natural situations. This study also contributes to confirm the hypothesis that the driver distraction can be evaluated by using the gap between eye movement simulation and measurement, made it possible to create a program that can detect the cognitive distraction while driving as an input for driver assistance system.

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List of Abbreviations

US NHTSA	**U**nited **S**tate **N**ational **H**ighway **T**raffic **S**afety **A**dministration
ADAS	**A**dvanced **D**river **A**ssistance **S**ystem
VOR	**V**estibulo **O**cular **R**eflex
OKR	**O**pto**k**inetic **R**esponse
MWLL	**M**ental **W**orkload
WHO	**W**orld **H**ealth **O**rganization
HR	**H**eart **R**ate
ECG	**E**lectro **C**ardiogram
HVR	**H**eart **R**ate **V**ariability
MSE	**M**ean **S**quare **E**rror
NRMSE	**N**ormalization **R**oot **M**ean **S**quare **E**rror
GA	**G**enetic **A**lgorithm
HGA	**H**ybrid **G**enetic **A**lgorithm

CHAPTER 1:   INTRODUCTION

1.1.   Background

1.1.1. Traffic accident

According to the World Health Organization (WHO) in 2015, over 1.25 million people die on the world's road and 90% of the world's fatalities on the roads occur in low- and middle-income countries.
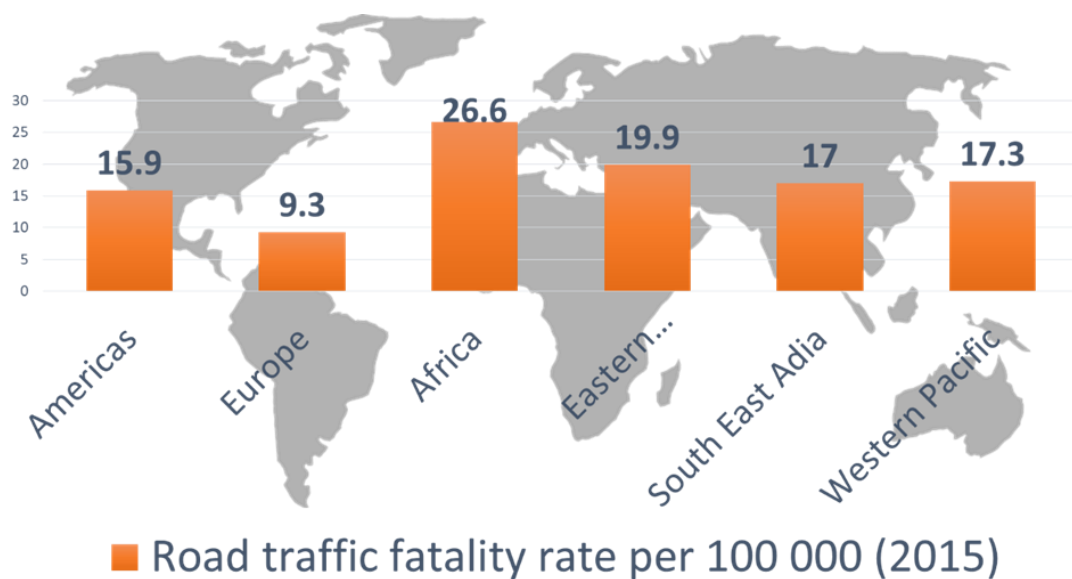
Source: World Health Organization

Figure 1-1. Road traffic fatalities per 1000 000 population

On the other side, in the developing country, the total of traffic accident still increases along with the increase of the demand for transportation. For example, In Vietnam, approximately 14,000 people die every year in the traffic accident. "Traffic-related accidents in every three years kill as many people as pandemic diseases do in 100 years," said by Nguyen Thien Nhan, Chairman of the Central Committee of the Vietnamese Fatherland Front, as cited by local media.

According to WHO, the main reasons of traffic accident are: speeding, driver under with alcohol or psychoactive substances, nonuse of protecting equipment such as helmets, distracted driving, unsafe road infrastructure, unsafe vehicle, and so on.

Nowadays, with the development of technology, especially in bioengineering, the total number of traffic accidents in the world has tendency to decrease by using an advanced driver assistance system (ADAS).

1.1.2. Advanced driver assistance system (ADAS)

Currently, with the development of technology, there are various devices such as radio, navigation, CD player, video recorder, television, and so on installed in the vehicle, which can bring the newest information from around the world to the driver. However, in the opposite side, it makes the driver not focusing on driving, which is the main course of traffic accidents. With the main purpose to assist the driver with monitoring, warning, braking and steering tasks, the advance driver assistance systems have been proposed.

For example, adaptive cruise control (ACC) that can automatically slow down or speed up your own vehicle based on the preceding vehicle, is a very useful system on the highway. By detecting the speed of other vehicles using laser or radar sensor, this system will adjust the position of throttle without using pedal or activating the brakes in emergency situations (Figure 1-2).

Source: http://1car.ir/ns-18
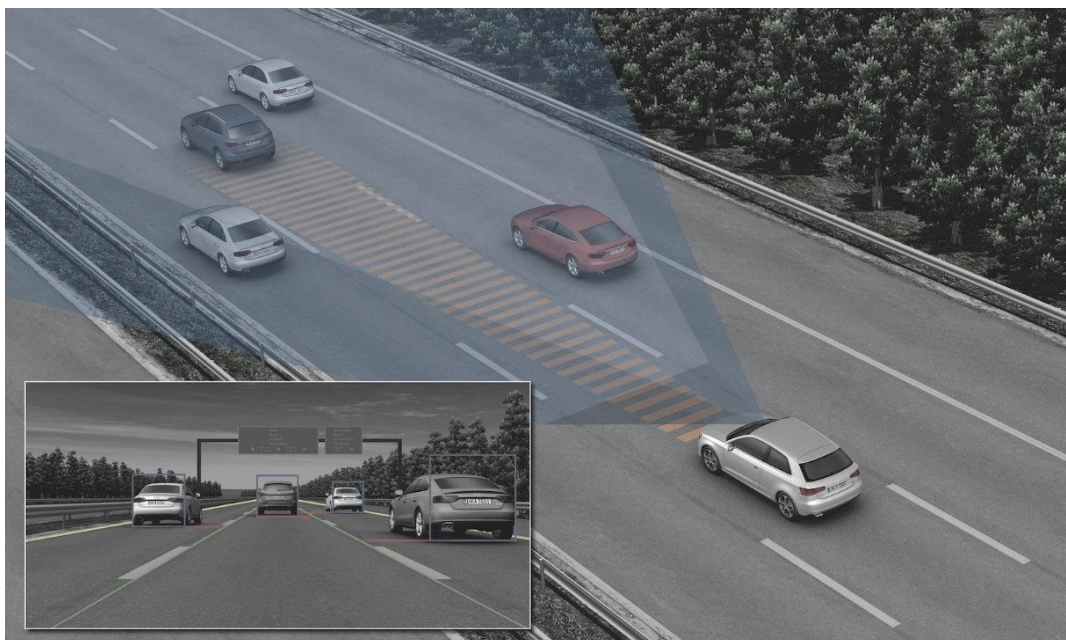
Figure 1-2. Adaptive cruise control system

According National Highway Traffic Safety Administration (NHTSA) – United States department of transportation (US-DOT), human error accounts around 90% of all traffic accidents, which almost cause by driver distraction. With the technology development makes it possible to create a new ADAS system which can capture driver distraction and prevent the accident.

1.1.3. Driver distraction

As reported by NHTSA (Ranney 2008), there were several definitions for driver distraction such as Pettit et al.: Distraction is "attention given to a non-driving-related activity, typically to the detriment of driving performance" (Pettitt et al. 2005). Because the brain were limited in attending to multiple task at the same time, therefore, the driver cannot focus on driving with doing some task (M. A. Regan, J. D. Lee 2008).

Distracted while driving is any activity that diverts attention from driving, including eating, texting, talking, drinking, using mobile, or other things that takes your attention away from the task of safe driving.

As reported by the NHTSA, there are three types of driver distraction:

- Visual: taking your eyes off the road;
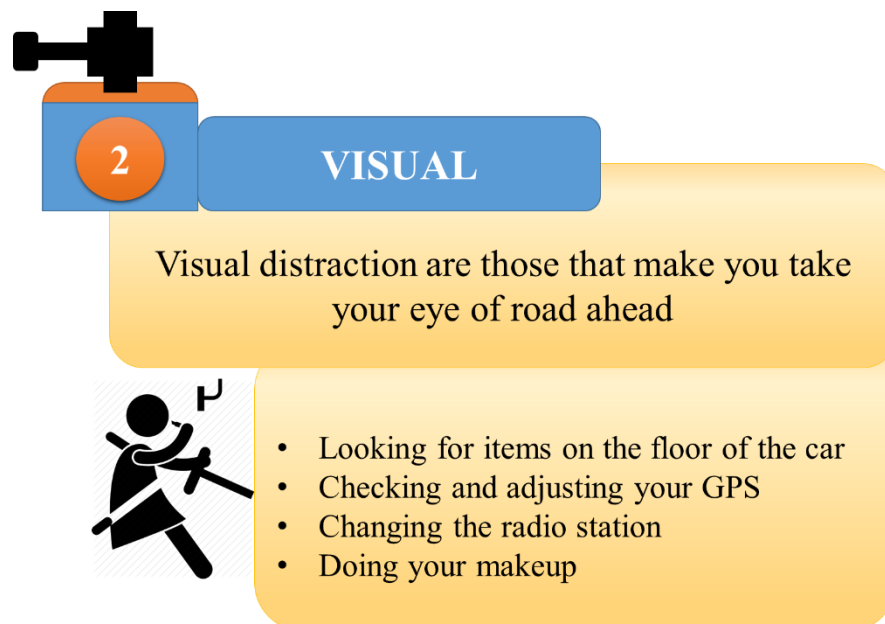
Figure 1-3. Visual distraction

-       Manual: taking your hands of the wheel; and

MANUAL

2

Manual distraction are those that require you to take one or more hands off the wheel.

- Eating and drinking
- Adjusting your child's seatbelt
- Smoking
- Searching through your purse or wallet
- Turning knobs in your car
- Control other device
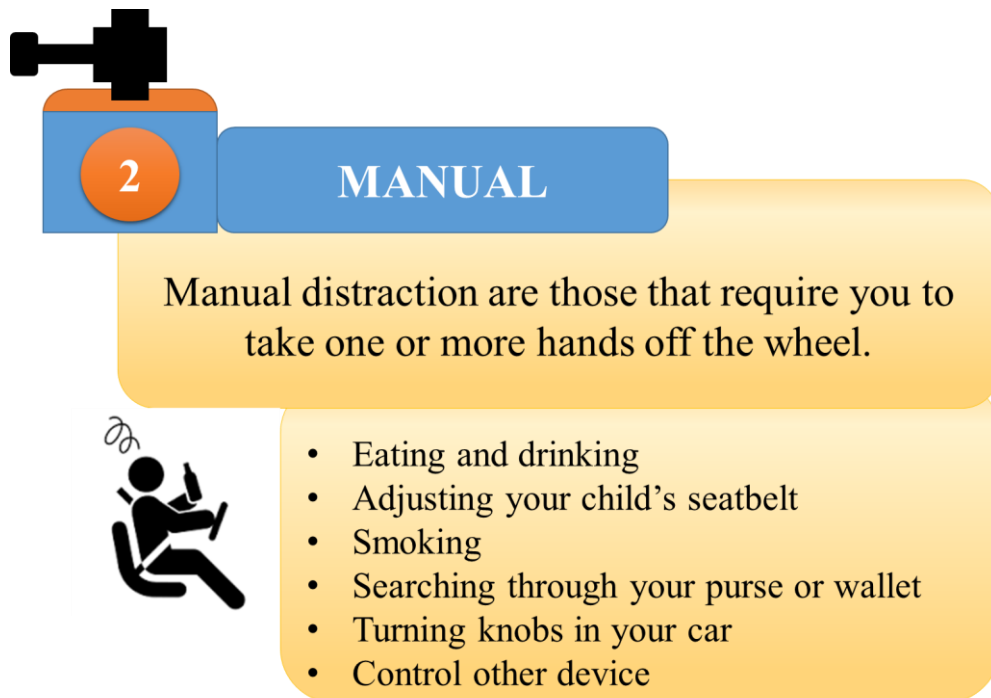
Figure 1-4. Manual distraction

-       Cognitive: taking your mind off driving

Cognitive

3

Cognitive distraction are those that keep your mind from focusing on the road

- Talking to another passenger
- Thinking about something that is upsetting
- Road rage
- Daydreaming
- Being under the influence of drugs and/or alcohol
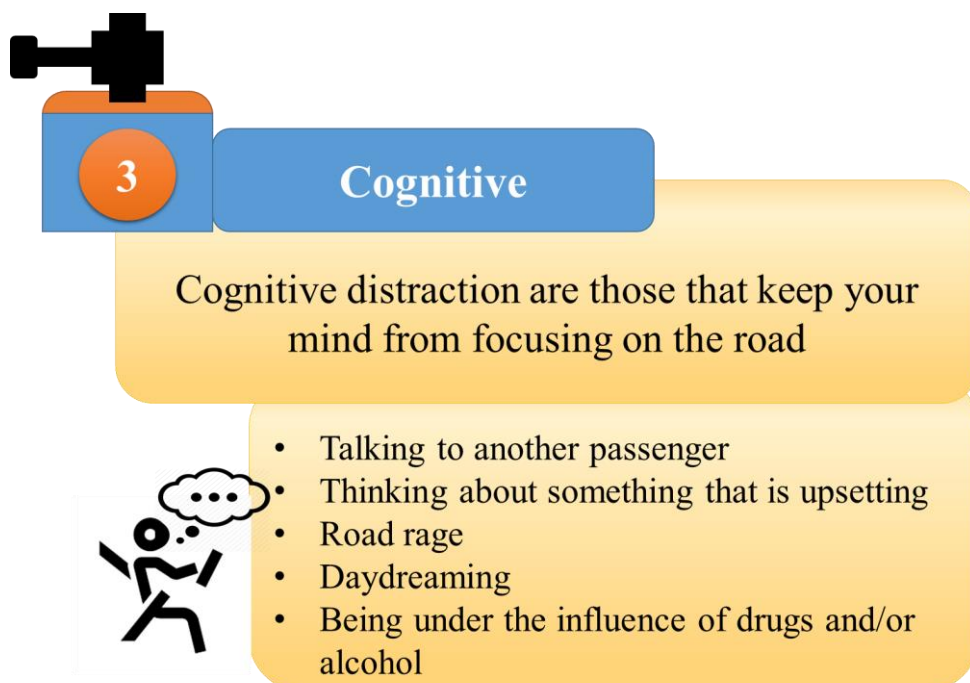
Figure 1-5. Cognitive distraction

1.1.4. Driver cognitive distraction

According to AAA Foundation for traffic safety (Strayer et al. 2000), the cognitive distraction occurs when the attention is withdrawn from the processing of information necessary for the safe operation of the vehicle. This type of distraction works independently with other ones, and this is the most difficult ones to capture because it observes by the driver's brain.

The mental resources required to perform a task are cognitive workload. The cognitive workload will lead to the cognitive distraction by diversion of mental resources from driving in dual-task conditions. And it leads to the increase of crash risk when impairments to driving from dual-task performance. For example, using a mobile phone or text while driving. This secondary task was required mental resource to perform. Besides that, it reduces the mental resource using for driving and late to recognize the objects.

1.2. Problem statements

Driver distraction, especially cognitive distraction plays very important role in reducing traffic accident. With the developed by the technology, more and more applications to support information will install in the vehicle which is one of the causes of distraction. To reduce the crash cause by driver distraction, beside the rule and advice for the driver, the assistance system for detecting driver distraction and prevent the crash is necessary.

Previously findings on evaluating the driver distraction has pointed out that under the distraction, the eye movement was unpredictable. However, the accuracy of the simulation in case of without mental workload is not good enough to apply it in case of changing the gaze or in the real situation.

1.3. Objective

The main objective of this research is to improve the methodology that is possible to detect driver cognitive distraction based on simulating eye movement even in a real situation. Based on that, hopefully, the assistance system will be created to avoid traffic accident cause by detecting driver distraction.

1.4.   Research Outline

As described in the next Chapter, the existing method is not precise enough to simulate eye movement in the actual situation with changing gaze and the changing of the environment. Therefore, to detect driver distraction, the eye simulation model will be developed. Based on the difference of simulation and measurement, the driver distraction can be indicated. The model based approach present in figure 1-6.
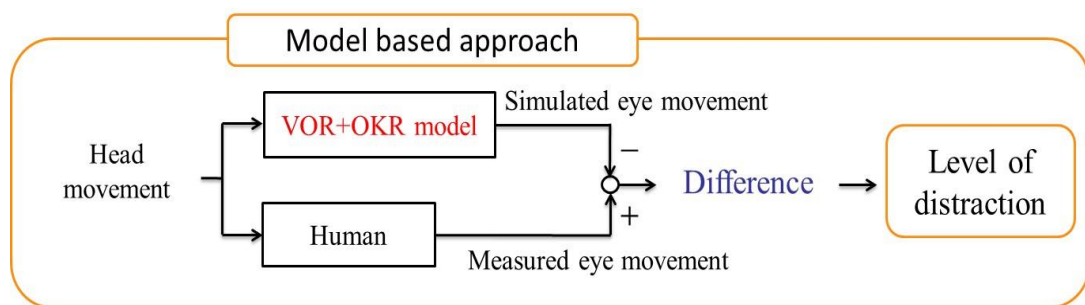
Figure 1-6. Model based approach

The development process is based on two important steps: the first, the parameter identification toolbox for Vestibulo Ocular Reflex (VOR) model will be developed by using genetic algorithm. Secondly, to reduce the effect cause by optic flow, the model will be developed by adding optokinetic response (OKR) model (Figure 1-7).
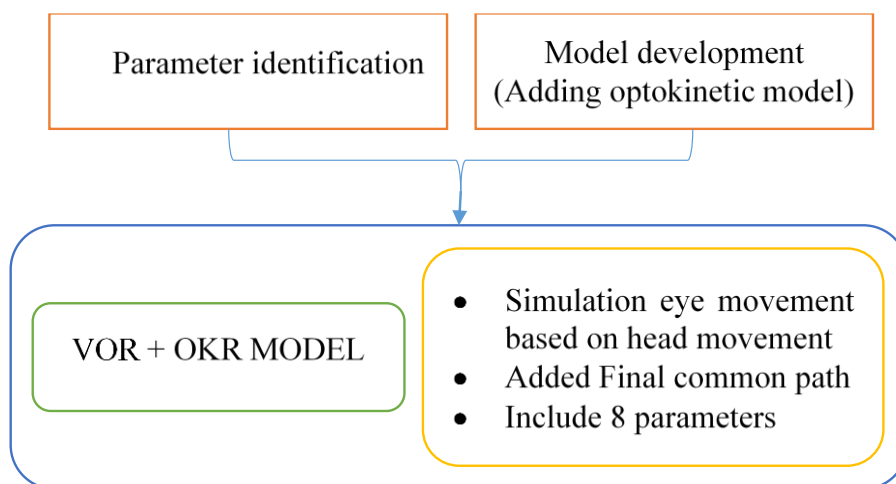
Figure 1-7. Research outline

Furthermore, to validate the development model, the experiment is conducted not only in a driving simulator but also in real situations. Approval of the experimental procedure was obtained from the Ethics Committee of Nagoya University's Institute of Innovation for Future Society. The results of the experiment are presented in Chapters 4, 5, 6, and 7.

CHAPTER 2:   EYE MOVEMENT AND IT'S APPICATION

2.1.   Eye movement

Eyes basically move based on a system of six extraocular muscles, including lateral, medial, inferior, superior, superior oblique, and inferior oblique muscle (Figure 2-1).
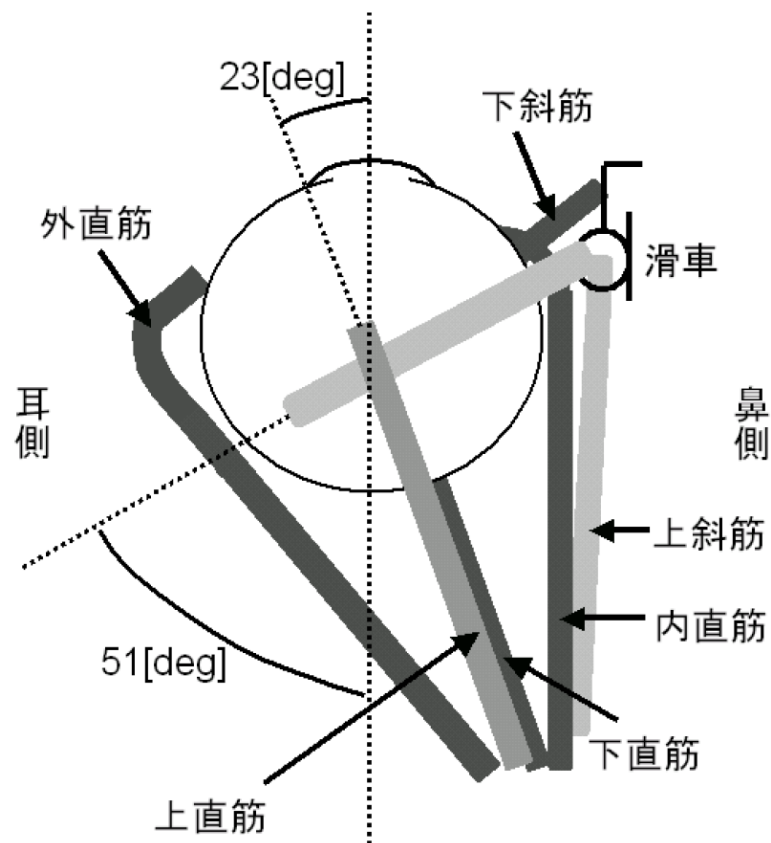
Figure 2-1. Extraocular muscle

The signal will be transmitted from the brain through cranial nerves (oculomotor nerve, trochlear nerve, and abducens nerve) to extraocular muscles.

2.1.1. Anatomy of the eyeball

Figure 2-2 shows the detail of eyeball anatomy. For perception, the light goes into the eyeball through the iris, lens, and stop in the retina, two different types of photoreceptors will capture the color (cones) and the light (rods). And then, the visual data are processed and sent to the brain.

Eyeball organizes from several parts such as cornea, pupil, iris, retina, and so on. Each part has the different mission, which is contributed to capture the visual and sent this signal to brain for processing.
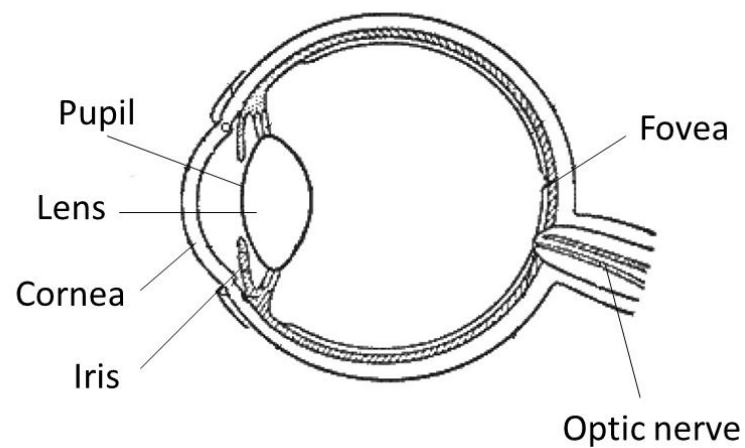
Figure 2-2. Eyeball anatomy

Cornea: is the front part of the eye. It is covered iris, pupil, and anterior chamber. The cornea contains five layers: corneal epithelium, bowman's layer, corneal stroma, Descemet's membrane, and corneal endothelium. The cornea contributes the eye's focusing power.
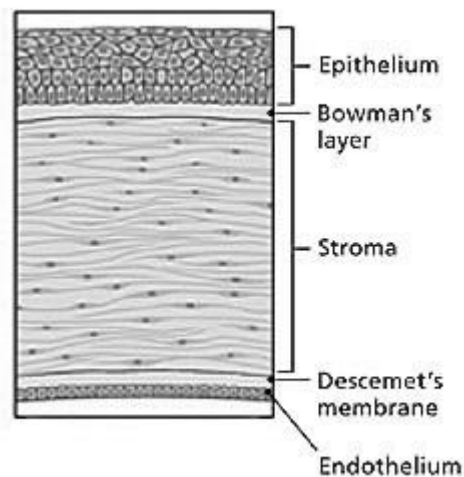
Figure 2-3. Cornea anatomy

Sclera: which contains collagen and elastic fiber is continuous with the clear cornea. It is the opaque, fibrous, protective outline layer of the eye. The sclera form has three divisions: episclera, sclera proper, and lamina fusca.

Retina: is the light-sensitive tissue lining of the eye. By using the optic nerve, the light rays will be converted into impulses and travel to our brain. The retina forms ten distinct layers: Inner limiting membrane, nerve fiber layer, ganglion cell layer, inner nuclear layer, outer plexiform layer, outer nuclear layer, external limiting membrane, layer of rods and cones, and retinal pigment epithelium.

Lens: is a transparent that retract light to be focused on the retina. The focus distance will change based on the changing of the shape of the lens.
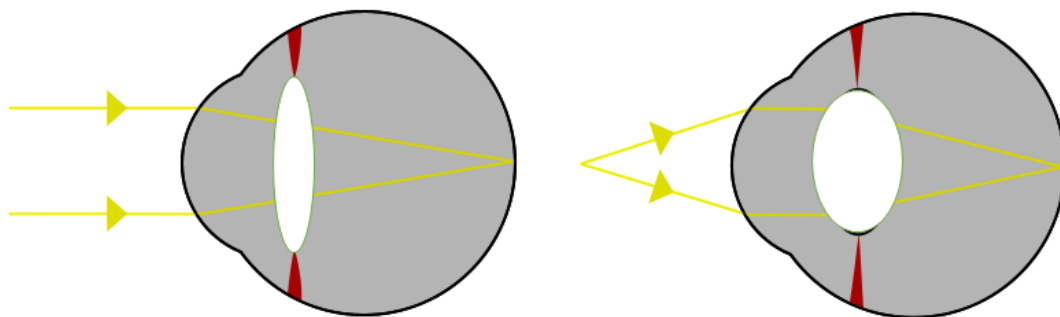
Figure 2-4. Lens

Optic nerve: with mission to transmit visual information from the retina to the brain, the optic nerve also knows as second cranial nerve. The length of the optic nerve from the eye to the chiasma is 35-55 mm that depends on the individual. The optic nerve contains four parts: optic nerve head, intraorbital part, intracanalicular part, and intracranial part.
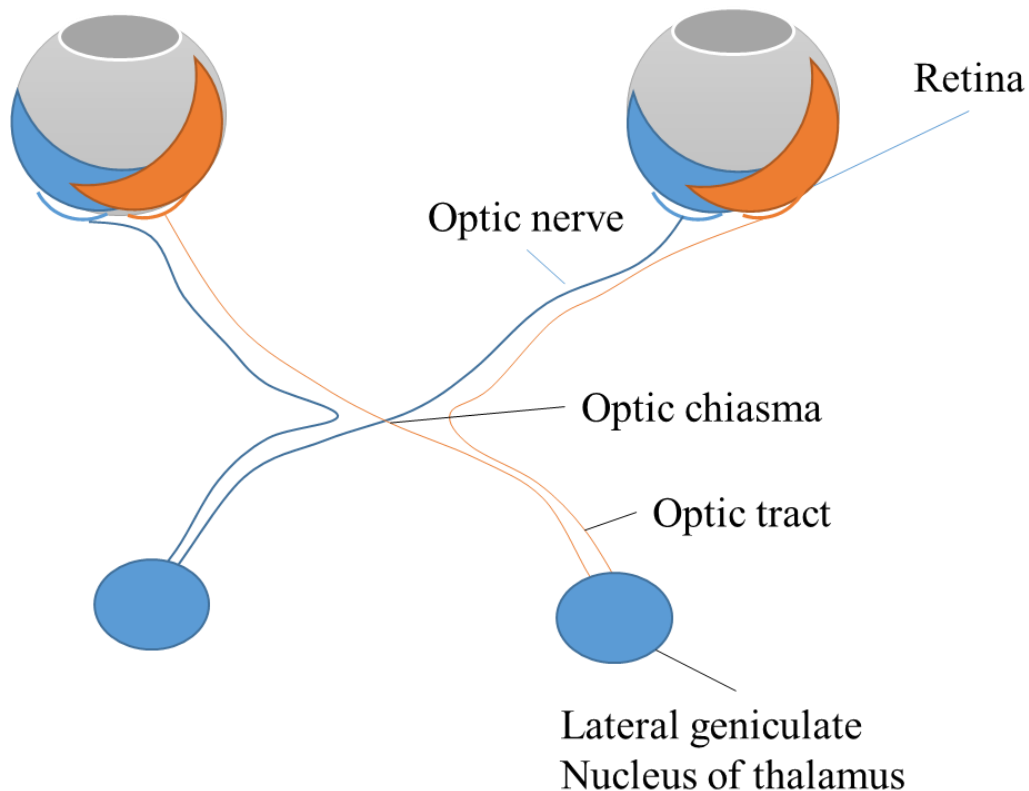
Figure 2-5. Optic nerve

Iris: is a part of the eye, which adjust circular opening in the center called a pupil. The iris has two layers: pigmented fibrovascular and beneath stroma. The iris is the main part to decide the eye color of each individual.

2.1.2. Eye movement

The main arm of eye movement is an acquirer, fixation, and tracking visual stimulus. Depend on the system, eye movement can be classified in several ways:

-   According to the involvement of one or both eyes: one eye as duction, both eyes as version, if moving the same direction or vergence, if moving in the opposite direction.

- It also can be classified as fixation, gaze stabilizing (include vestibule-ocular reflex and optokinetic reflex), or gaze shifting (include saccades and pursuit movement).

Saccades

Saccades is one type of eye movement that include hypometric saccades, dysmetric saccades, glissadic eye movement, slow saccades, overlapping saccades, dynamic overshoots, closely spaced saccades, and pulseless saccades (A. Terry & B. Todd 1979). With extremely fast rotation of two eyes, the peak angular speed of eye reaches up to 900o/s during saccades.

Pursuit movement

Smooth pursuit movement is a low tracking movement where the eye closely follows an object. The Pursuit eye movement has two stages: open-loop pursuit and close-loop pursuit.

Optokinetic response (OKR)

OKR works with the main purpose to move the eye back to the first position when it follows the moving object. OKR has two phases: slow-phase and fast-phase.

Vestibulo-ocular reflex (VOR)

VOR is one of reflex response that stabilize the eye when the head movement to remain focused on a target.

2.2. Eye movement application in Transportation

The eye, the key point of the driver, plays very important role in transportation, has wide numbers of applications in medicine. Most applications use the pupil response and gaze control.

According to the previous researches, the pupil diameter can indicate the cognitive load (Iqbal et al. 2004) (King-Smith & Rose 1997) (Bailey et al. 2007) (Klingner 2010) (Wang et al. 2010) (Klingner et al. 2008) (Backs & Walrath 1992) (Just et al. 2003) (Schwalm et al. 2008) (Müller et al. 2016) (Iqbal et al. 2004) (Rosch & Vogel-Walcutt 2013) (Kramer 1990) (Backs & Walratht 1992). Based on their results,

the cognitive load increase, the pupil size also growth. However, due to the sensitivity of the pupil, the brightness may affect the pupil diameter as same as cognitive workload. On the other hand, the pupil size is also applied for behavior detection or adaptation to the environment (Allard et al. 2011) (Wang et al. 2010).

The gaze application by using gaze direction, fixation duration, and saccades, is used for indicating the cognitive load in general (Murray et al. 1998) (Reimer & Sodhi 2006) (Di Stasi et al. 2010) (Irving et al. 2009) (Klingner 2010) (Robinson et al. 1986) (Niezgoda et al. 2015) (Watten & Lie 1997). Besides that, the gaze application is also applied for reading comprehension (Mitchell et al. 2010), presentation design (Bruny & Taylor 2009), distraction and attention guiding (DeLeeuw et al. 2010), and human-computer interaction (Møllenbach et al. 2010).

CHAPTER 3:   LITERATURE REVIEWS

3.1.   Information processing of mental workload

According to the previous studies, mental workload has wide and various concepts. Most of them focus on the concept that mental workload was limited processing capacity (Egeth & Kahneman 1975) (Norman & Bobrow 1975) (Posner 1978) (Wickens 1991). As mentioned by Norman and Bobrow (1975), when added secondary task, the primary task negatively correlate with the difficulty of the secondary task.
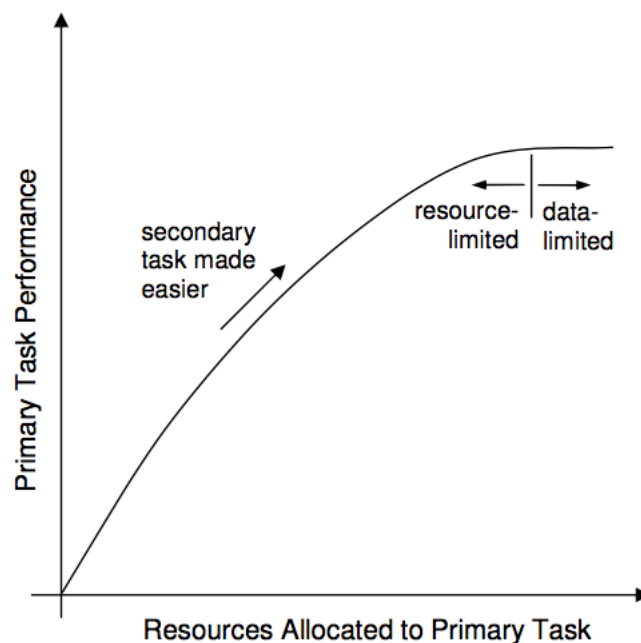
Figure 3-1. Allocated to the primary task

Wickens proposed the model for multi resource theory. In their research, the pools of resources were defined in four dimensions: Perception modality, code processing, processing stage, and a response type (Wickens 1991) (Wickens & Hollands 1999).
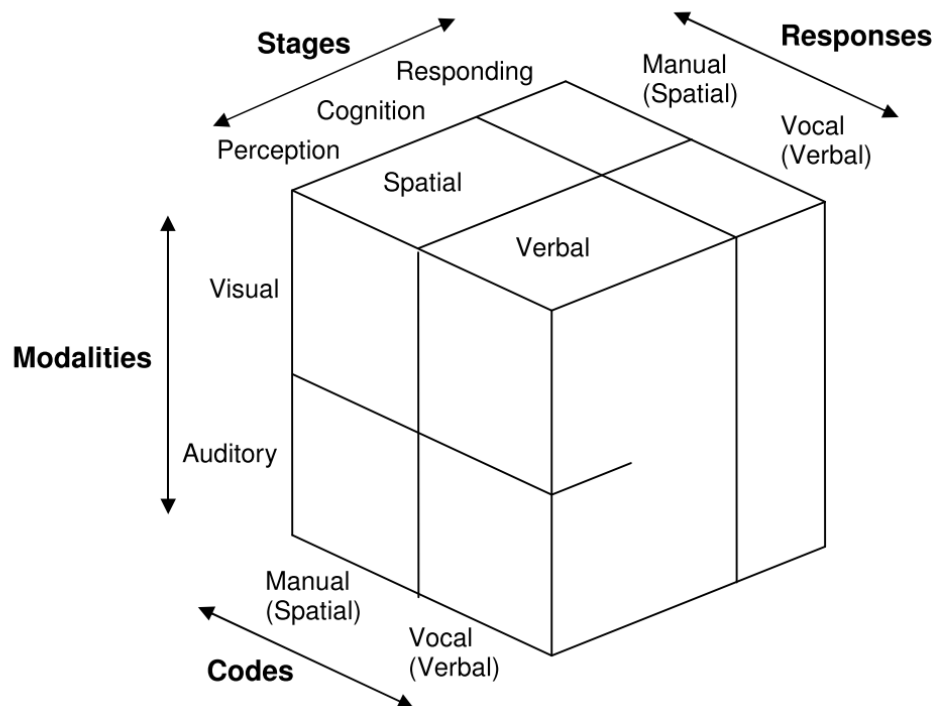
Figure 3-2. Multiple resource theory [Wickens 1984]

In mapping between cognitive with choice reaction tasks, the model of information processing was proposed by Sanders (1983). In his research, the energetically supply mechanisms were divided into three parts: arousal, activation, and coupled. For more detail, please refer Picture 3-3.
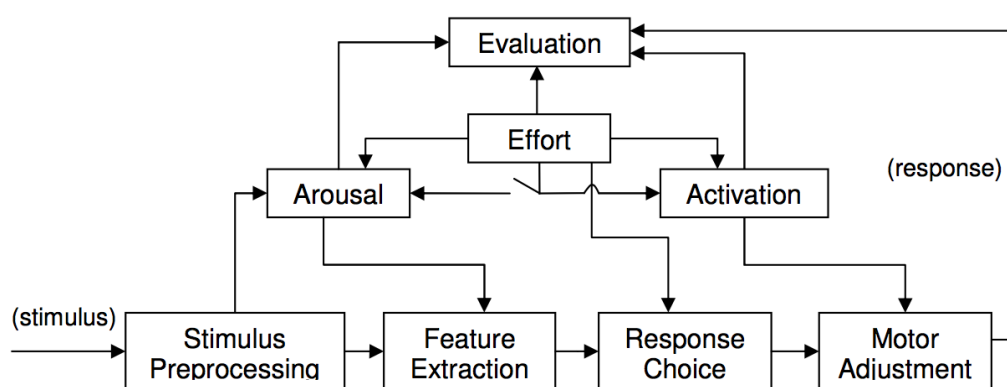
Figure 3-3. Cognitive-energetically model proposed by Sanders (1993)

In summary, the mental workload is occurred when the person does a couple of tasks difficultly (Gopher & Donchin 1986). Due to each situation, the operator can adapt their behavior by reducing the performance or giving up other tasks to focus on the main task (Meijman & O'Hanlon 1984).

Focusing on transportation aspect, the driver workload already appeared from 1985 (Michon 1985) and became a popular topic to discuss. According to several researchers, during driving, the driver has to do multiple task, such as making decisions, route choice, behavior with other traffic participant, processing traffic environment information, and so on (Land 2006) (Platten 2012) (Faure et al. 2016a). The source of driver workload is not only from the inside, but also the outside of the vehicle. Several information such as driver state, driver trait, and environment can be useful to estimate drivers' mental workload (Faure et al. 2016b) (Platten 2012) (Anh Son et al. 2016) (Recarte & Nunes 2003) (Patten et al. 2004) (DiDomenico & Nussbaum 2011) (Makishita & Matsunaga 2008) (Brookhuis & de Waard 2010) (Charlton et al. 2013) (Hancock et al. 1990) (Wickens 2008) (Veltman & Gaillard 1996) (Brookings et al. 1996) (Young & Stanton 1997) (Tsang & Vidulich 2006).

3.2. Mental workload measurement

Based on the previous researchers, the mental workload measurement can categories into three groups: subjective measures, performance – based measures, and physiological measures.

3.2.1. Subjective measure

In the past, there was a lot of studies using this method to evaluate mental workload (Hart & Staveland 1988) (Reid et al. 1989) (Widyanti et al. 2013) (Zijlstra 1993). This method is basically based on asking the participant for rating their effort. This methodology contains a huge of limitation such as: not correlate with task performance (Gopher & Braune 1984), depend on working memory (O'Donell & Eggemeier 1986) (Tsang & Vidulich 2006), and so on.

3.2.2. Performance-based measure

The performance measure can be categorized into three groups (De Waard 1996): primary-task measure, secondary-task measure, and reference tasks. The primary task measure is the measurement of error made by tracking the performance. However, this methodology still contains some of limitation such as: the difference of performance between two operators cannot be determined (O'Donell & Eggemeier 1986). This method should be combined with other ones to have the conclusion about man-machine interaction.

By adding a secondary task measure, this method become multi task performance, however, the limitation still cannot be solve compare with previous ones.

On the other hand, this method was very difficult to apply in transportation, especially for capturing driver distraction because the delay may cause to driver accident.

3.2.3. Physiological measure

With the limitations are equipment (specialized one), technical expertise, and the noise from the signal (Kramer 1990), but this methodology is the most powerful technique that is possible to apply in the commercial market. This method uses the difference or the sensitivity of body sensory information to predict mental workload by capturing the actual one.

· Electrocardiogram (ECG)

Heart rate (HR) is one important signal, which can indicate mental workload by using the difference of HR during task performance and rest-baseline (Porges & Byrne 1992). Because of the sensitivity, the heart rate variability (HRV) signal was combined to evaluate the mental workload (Lee & Park 1990) (Henelius et al. 2009) (Meshkati 1988) (Cinaz et al. 2013) (Veltman & Gaillard 1996) (Ryu & Myung 2005).

In contrast, age, physical fitness level, body position, muscle activity, and respiration patterns has strong influence on HRV (Jorna 1992). Therefore, to apply in the real situation with multiple tasks and the activity of muscle like driving, this method may be difficult to detect mental workload.

· Eye blinks

Blink rate, blink duration, and blink latency have the relationship with mental workload (Benedetto et al. 2011) (Tsai et al. 2007). However, in driving under dual-task conditions, eye-blink behavior was not a clear indicator of mental workload (Veltman & Gaillard 1996).

· Pupil diameter

Pupil diameter has strong relationships with mental workload. According to several researches in the past, the pupil diameter increases with increases in perceptual, cognitive, and response-relate processing demand (Wang et al. 2010) (Klingner et al. 2008) (Backs & Walrath 1992) (Klingner 2010) (Schwalm et al. 2008) (Backs & Walratht 1992). However, pupil diameter also has a strong effect of the light that shows a remarkable change while driving (Palinko & Kun 2012).

· Saccadic Eye Movement

As reported by several studies, the saccadic eye movement or intersaccadic interval can capture the mental workload (Tokuda et al. 2009) (Pierce 2009) (Tsai et al. 2007) (Pierce 2009). However, in case of driving, with the complex environment, variable tasks, applying saccadic to online capture mental workload are still a challenging.

· Vestibulo Ocular Reflex model

One method that has considerable potential for the evaluation of driver distraction uses the difference between observed and simulated eye movements (Usui et al. 2007) (Obinata et al. 2008) (Obinata et al. 2009). In their research, Usui et al. found a relationship between driver distraction and involuntary eye movement. However, the model needs to be improved if it is to be applied under realistic driving situations involving voluntary eye movement.

To apply this method to realistic driving situations, the parameter identification should be improved. On the other hand, the combining an OKR model with a VOR model is necessary to simulate eye movement.

3.3. Mental workload measurement while driving

According to T.W.Schaap et al. (2013), mental workload and driver distraction are different phenomena, but they are strongly related. In case that the driver is more focused on the primary driving task correctly and safely, the mental workload increases, inversely, the driver distraction is sustainable. However, in performance of safe driving such as a secondary task, the mental workload and distraction are highly similar. In this study, we only concern about driver safety aspect, therefore, the drivers' mental workload can be assumed as driver distraction.

As mentioned in Chapter 1, the total number of accidents can be reduced by creating a new ADAS system which can online capture the driver mental workload and taking an action such as activating automatic braking system. To achieve that the methodology for evaluating driver distraction should be working well in actual condition.

In case of driving, the physiological method is suitable for detecting driver distraction. The proposal method should work in a complex environment, multiple tasks, the vibration, the noise when capturing the sensor signal (especially the attaching sensor), and several of working muscle. Moreover, in the aspect of collecting data, the random error will be appeared a lot with attaching device due to the sensitive of the sensor with the movement of the subjects. Inversely, for collecting the image and processing it, a partial error can be eliminated by the filter. Therefore, using eye movement would be one of the best methods for online evaluation of driver distraction.

Previously finding on eye movement has pointed out that there are two types of eye movement: voluntary eye movement and involuntary eye movement. The voluntary eye movement was included saccade, smooth pursuit; and the involuntary eye movement includes VOR and OKR. In previous works, there is some model which can simulate eye movement based on the head movement by combining VOR with OKR and smooth pursuit (Schweigart et al. 1999) (Merfeld et al. 2002) (Robinson 1981). However, for applying it for the driver in the real situation is still a challenging.

Figure 3-4. Integrate eye movement proposed by Schweigart et al. (1999)

Figure 3-5. Integrate eye movement proposed by Robinson et al. (1981)
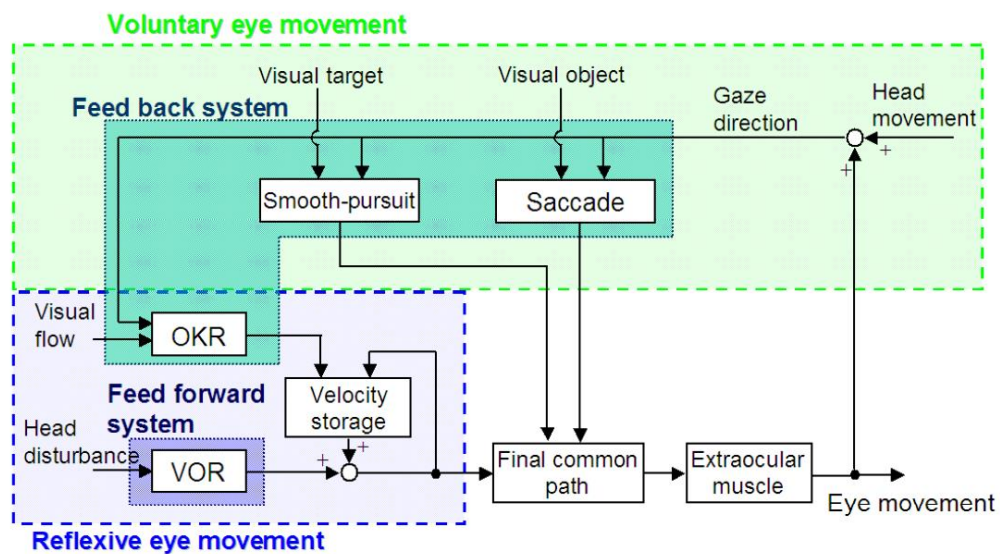
Figure 3-6. Eye movement model

The same for the driver, the eye movement model is presented in Figure 3-6. The input for simulating eye movement is: head movement, Visual information, and Target information. The signal from the input will be calculated in total with VOR model, OKR model, Smooth-pursuit, and saccade.

· Saccades

This type of eye movement will occur when the driver focuses on pedestrian, traffic signal, and traffic control, and so on with higher speed.

· Smooth Pursuit

Occurred when the driver looks following an object, normally in a horizontal.

· OKR

Stabilizing the image on the retina when the object moving

· VOR

Occurred when the driver focuses on target, but the head move due to the vibration of the vehicle.

While driving, the vibration always occurs, this vibration will be transmitted to the driver's head. Therefore, VOR always appear while driving and almost in vertical direction.

On the other hand, in vertical direction, the smooth-pursuit rarely appears.

Based on all of the evidence, for evaluating driver distraction, the most potential method was a VOR model combine with an OKR model to simulate eye movement in the vertical direction. By comparing with measurement eye movement, the difference about them can be indicated driver's mental workload.

3.4.   Vestibulo-Ocular reflex model

The vestibule-ocular reflex (VOR) is a reflex that inertial stabilization mechanism sub serves vision by producing eye movement in the direction opposite to the head movement (Stephen et al. 2004). In this model, the head acceleration is played as the stimulus that is detected by the vestibular apparatus of the middle ear.

The vestibular system is the sensory system that coordinates movement with balance by providing the leading contribution to the sense of balance and spatial orientation.

Semicircular canals

Utricle

Saccule

Scala tympani

Scala media

Scala vestibuli

Cochlea
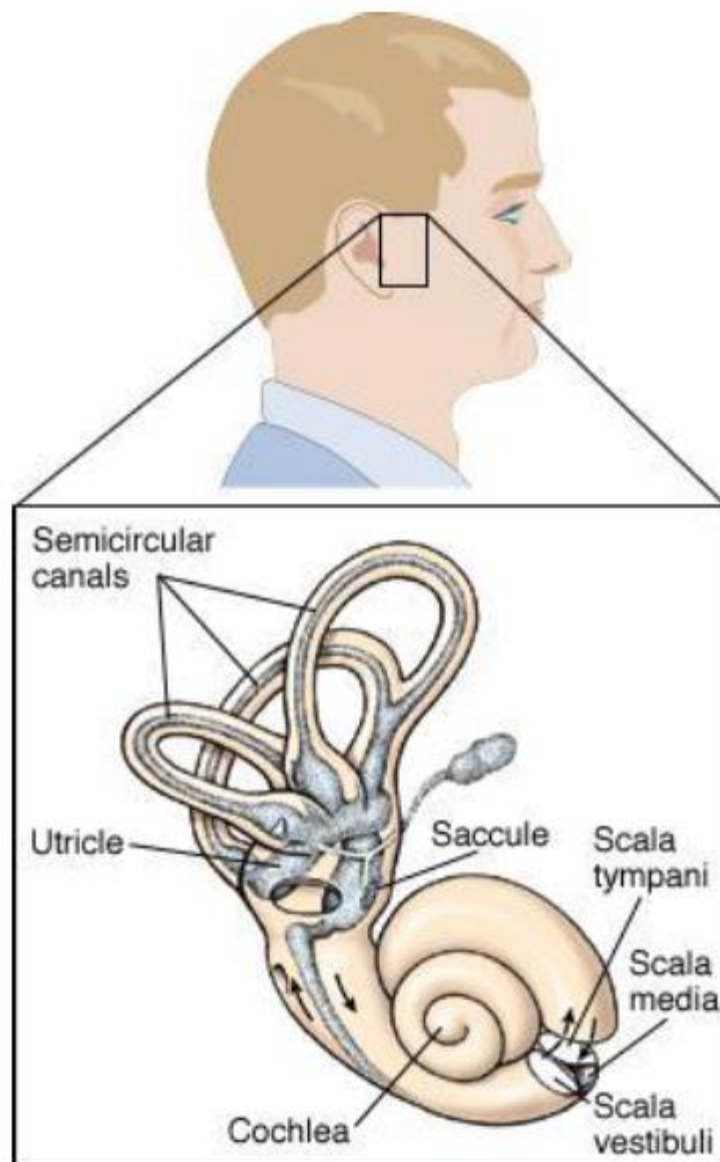
Source: Vestibular disorders association

Figure 3-7. Vestibular system

The main purpose of the VOR is to stabilize images on the retina during head movement by producing an eye velocity that is equal and opposite to head velocity. Figure 3-7 shows schematically how the VOR works during a horizontal head movement. Basically, the head movement is detected by the semicircular canals. And then this signal is sent to nucleus vestibular before fibers cross to the abducens nucleus by vestibular nerve and interneurons. At nucleus abducens, there are

synapses with 2 additional pathways: the first one direct to the lateral rectus, the second one via oculomotor nucleus to activate the medial rectus muscle.
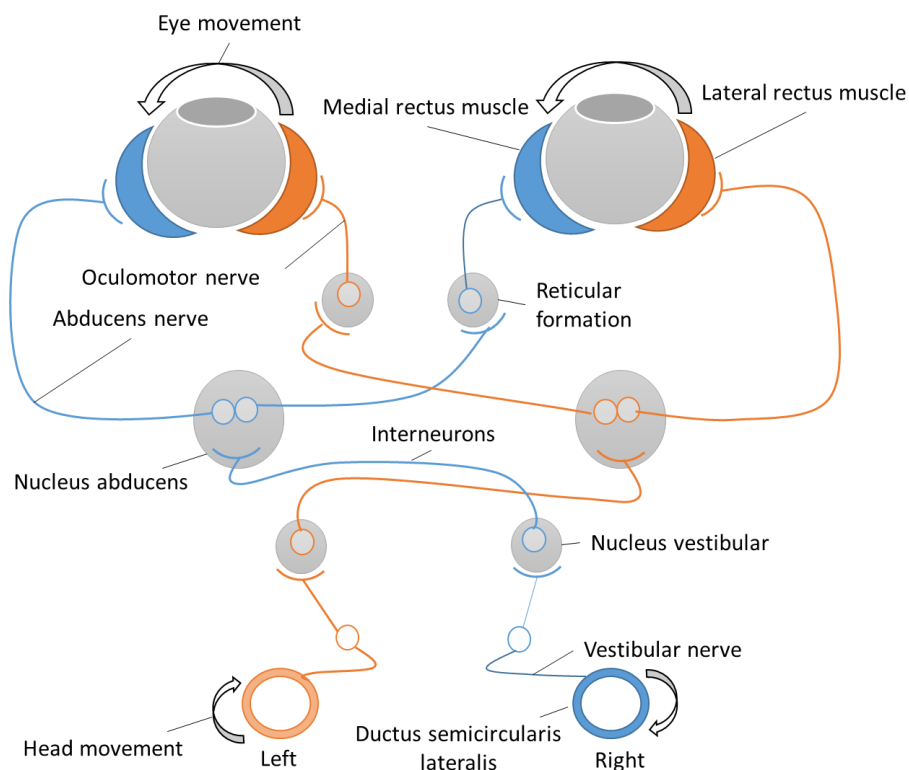
Figure 3-8. Schematic illustration of the three neural arc reflex of VOR

According to the results obtained by Zupan and Merfeld (Zupan & Merfeld 2003) and by Angelaki and co-workers (Green & Angelaki 2010) (Angelaki et al. 2000) (M. Green & Angelaki 2010) (Angelaki et al. 2001), the transformation of a vestibular signal into internal-motion parameters involves two main computations. In the first, angular-velocity signals from the semicircular canals (ω) are used to segregate the resultant linear acceleration signals coded by primary otolith afferents (α) into gravitational (g, orientation) and translational (f) components. In the second, gravitational estimates are used to transform head-fixed angular-velocity signals from the semicircular canals (ω) to the inertial velocity, i.e., the space-referenced angular velocity (ω_S).

Figure 3-9 shows the detailed blocks of the VOR model. The semicircular canals [which measure the angular velocity of the head (ω)] and the otolith organs [which measure linear accelerations of the head (α) and gravity (g)] sense the proprioceptive information from the environment; this is the first step in calculating

sensory information from the measurements (α_{oto}, α_{scc}). In the next step, the measurements are compared with the sensory information predicted by the internal model. This model combines four free parameters (k_ω, $k_{f\omega}$, k_f, and k_a). The parameter values were determined by the feedback of this error.
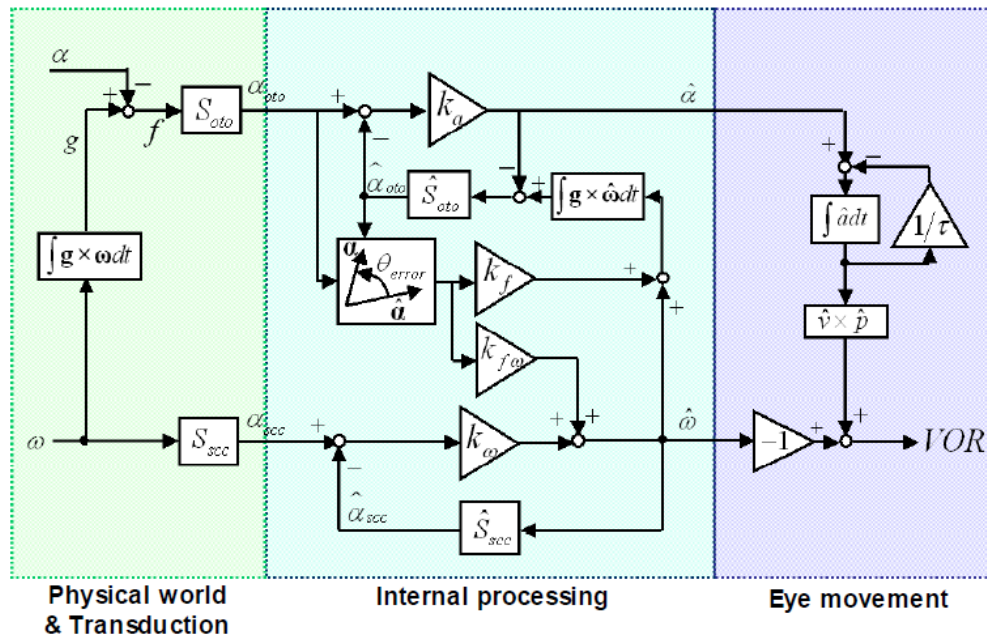
Figure 3-9. VOR model in MATLAB Simulink

Obinata and co-workers proposed a new method for online evaluation of driver distraction (Obinata et al. 2009) (Obinata et al. 2008) (Usui et al. 2007) (Obinata & Tokuda 2008). In their researches using a VOR model, eye movement was simulated on the basis of head movement. The coherence between simulated and measured eye movement was used as a metric for the level of distraction. However, these researchers did not consider the natural eye movement or the effect of visual information.

To deal with the interaction between otoliths and semicircular canals, in this study, we apply the VOR model proposed by Merfeld and Zupan. For more understanding about the mathematical, the VOR model was explained below by including three parts: physical world & sensor, internal processing, and eye movement:

(a) Head   (b) Eye ball
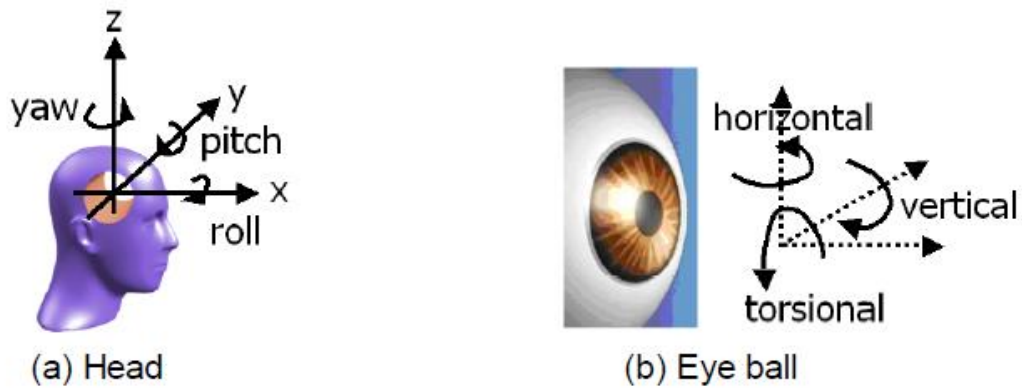
Figure 3-10. Definition of coordinate system

·   Physical world and Transduction

In this part, three dimensional vectors of linear acceleration (α) and angular velocity (ω) are input to the model in a head-fixed coordinator.

$$\alpha = [a_x \quad a_y \quad a_z]$$

$$\omega = \begin{bmatrix} \dot{\theta}_x & \dot{\theta}_y & \dot{\theta}_z \end{bmatrix}$$
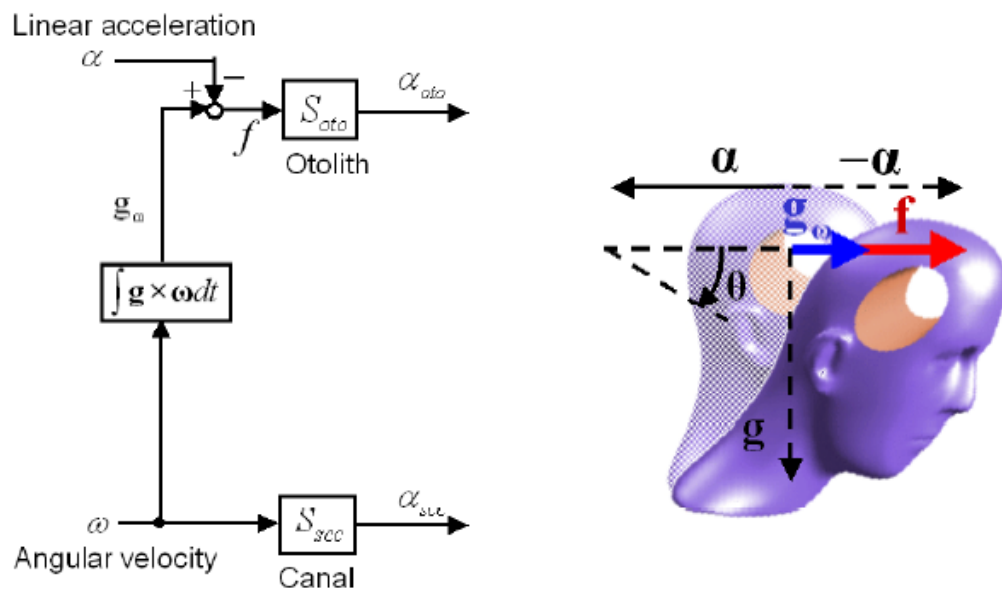
Figure 3-11. Physical world & transduction

By integrating angular velocity using a quaternion integrator ($\int g \times \omega dt$), the track of orientation of gravity (g) was keep with respect to the head.

$$\mathbf{f} = -\mathbf{a} + \mathbf{g}_\omega$$

$$\mathbf{g}_\omega = \int \mathbf{g} \times \omega dt = \begin{bmatrix} \theta_y G & -\theta_x G & 0 \end{bmatrix}$$

And then, the semicircular canals (Scc) are calculated as 2rd order high-pass filter with a cupula/endolymph long time constant of 5.7 seconds and a neural adaptation time constant of 80 seconds.

$$Scc = \begin{bmatrix} scc & 0 & 0 \\ 0 & scc & 0 \\ 0 & 0 & scc \end{bmatrix}$$

$$scc = \frac{\tau_a \tau_d s^2}{(\tau_a s + 1)(\tau_d s + 1)}$$

$$Soto = \begin{bmatrix} oto & 0 & 0 \\ 0 & oto & 0 \\ 0 & 0 & oto \end{bmatrix}$$

Where τ_d = 5.7 seconds, τ_a = 80 seconds, oto =1

After generating the signal from the canals and otolith, the signal will transfer to Internal processing part.

·   Internal processing part

In this part, the input was sensory input form otolith and canal, and the output were neural estimation (linear acceleration), neural estimation (gravity), and neural estimation (angular velocity). The detail of block is shown in figure 3-12.
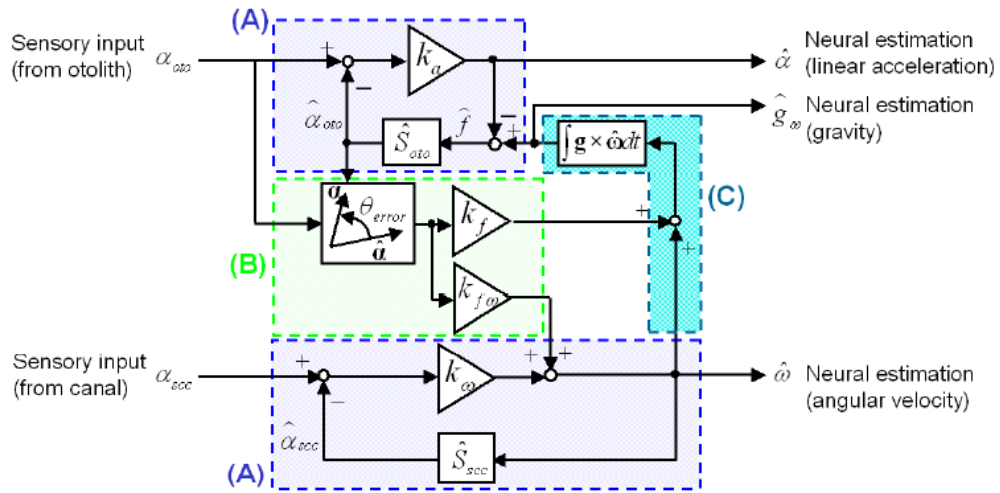
Figure 3-12. Internal processing

A.   Internal model of sensory dynamics & feedback loop

The error between the semicircular canal afferent signal (α_{scc}) and expected semicircular canal signal is multiplied by the velocity gain error (k_ω). On the other hand, the internal model of the canal geometry is assumed that is the same with actual canal models.

$$\hat{S}cc = \begin{bmatrix} \hat{s}cc & 0 & 0 \\ 0 & \hat{s}cc & 0 \\ 0 & 0 & \hat{s}cc \end{bmatrix}$$

$$\hat{s}cc = \frac{\tau_d s}{\tau_d s + 1}$$

$$\hat{S}oto = \begin{bmatrix} \widehat{oto} & 0 & 0 \\ 0 & \widehat{oto} & 0 \\ 0 & 0 & \widehat{oto)} \end{bmatrix}$$

B.   Error calculation
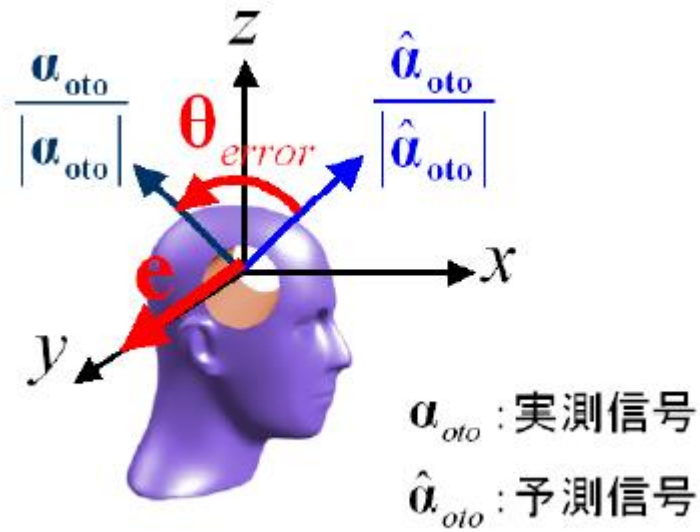
Figure 3-13. Error calculation

The model of the VOR contains three errors: the angular velocity error vector (e_ω), the linear accelerator error (e_α), and the GIF rotation error (e_f) (Merfeld et al. 2002) (Merfeld et al. 1993). The magnitude and sign of the error is calculated based on calculating the angle between the predicted and measured otolith cues (θ_{error}). The equation of dimensionless direction of the rotation (e) is shown below:

$$e = \frac{\widehat{\propto}_{oto}}{|\widehat{\propto}_{oto}|} \times \frac{\propto_{oto}}{|\propto_{oto}|}$$

$$\theta_{error} = \left(cos^{-1} \left(\frac{\widehat{\propto}_{oto}}{|\widehat{\propto}_{oto}|} \times \frac{\propto_{oto}}{|\propto_{oto}|} \right) \right)$$

C.   Influence of rotational cue on the neural representation of gravity

Similar to physical world & transduction, the equation of influence of rotational cue on the neural representation of gravity show below:

$$\mathbf{f} = -\mathbf{a} + \mathbf{g}_\omega$$

$$\mathbf{g}_\omega = \int \mathbf{g} \times \mathbf{\omega} \, dt = \begin{bmatrix} \theta_y G & -\theta_x G & 0 \end{bmatrix}$$

·   Eye movement part
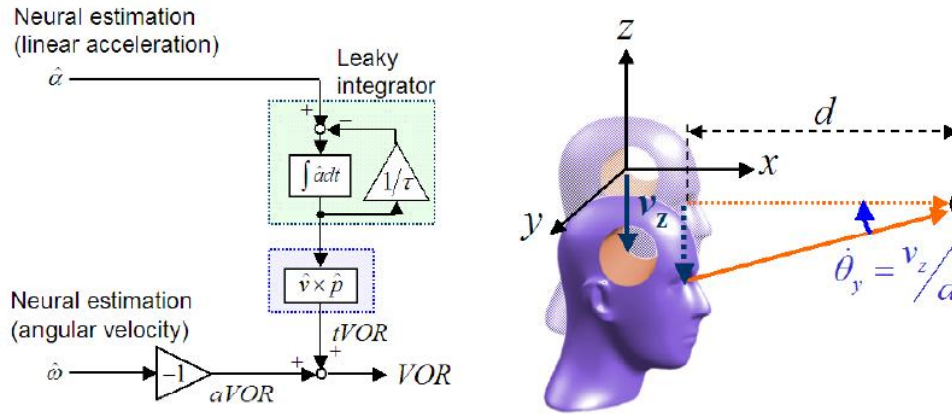
Figure 3-14. Eye movement

After internal processing part, the neural estimation in both linear acceleration and angular velocity was used to transfer to aVOR (rotation) and tVOR (translation). The sum of them is VOR. The detail of mathematical show in equation below:

$$\hat{p} = \begin{bmatrix} 1/\hat{d} & 0 & 0 \end{bmatrix}$$

$$\hat{v} \times \hat{p} = \begin{bmatrix} 0 & \widehat{v_z}/\hat{d} & -\widehat{v_y}/\hat{d} \end{bmatrix}$$

3.5.   Optokinetic Response model

Optokinetic response which the role is cooperation with VOR to keep the image stabilization on the retina during head rotation in stationary visual surround, is a combination of slow-phase and fast-phase eye movement.

The optokinetic model was developed by several researchers to simulate eye movement based on head movement by combining OKR and VOR (Schweigart & Mergner 1995) (Schmid et al. 1979) (Schweigart et al. 1997) (Kerkhoff et al. 2006) (Lappe et al. 1998) (Harvey et al. 1997) (Hain 1986) (Mestre & Masson 1997) (Clark et al. 2015a) (Merfeld et al. 1993) (Rader et al. 2009).

According to Robinson (Robinson 1981) and Schweigart & Mergner (1997), on the visual scene, the eye movement simulation requires to combine actions of the vestibulo-ocular reflex (VOR; eye stabilization in space) and the optokinetic response (OKR; eye stabilization on the visual scene).

In most previous researches on the OKR-VOR interaction, passive and active head movements were used. The effect of active head rotation may be enhanced if the optokinetic input is modified by magnifying spectacles (Demer et al. 1993). By using active and passive head movements, Schweigart & Mergner created the relationship between visual pattern motions in space with the subject's head movements. Based on that information, the negative feedback loop was made to stabilize image on the retina and the VOR only as a useful addition which compensates for the limited bandwidth of the OKR during high frequency/velocity head rotations.

On the other hand, Newman (2009) and Clark et al. (2015b) (2015a) dealt with the interaction between VOR and OKR by including static and dynamic visual sensory information from four independent visual sensors (visual velocity, position, angular velocity and gravity). The process of visual input is shown in Figure 3-15.
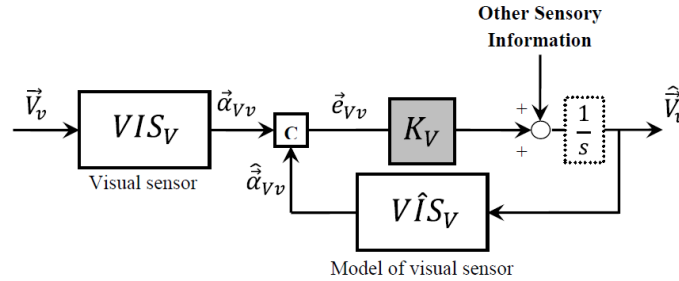
Figure 3-15. Generic visual model path way proposed by Newman

For more details, Figure 3-16 will show the interaction between visual and vestibular model.
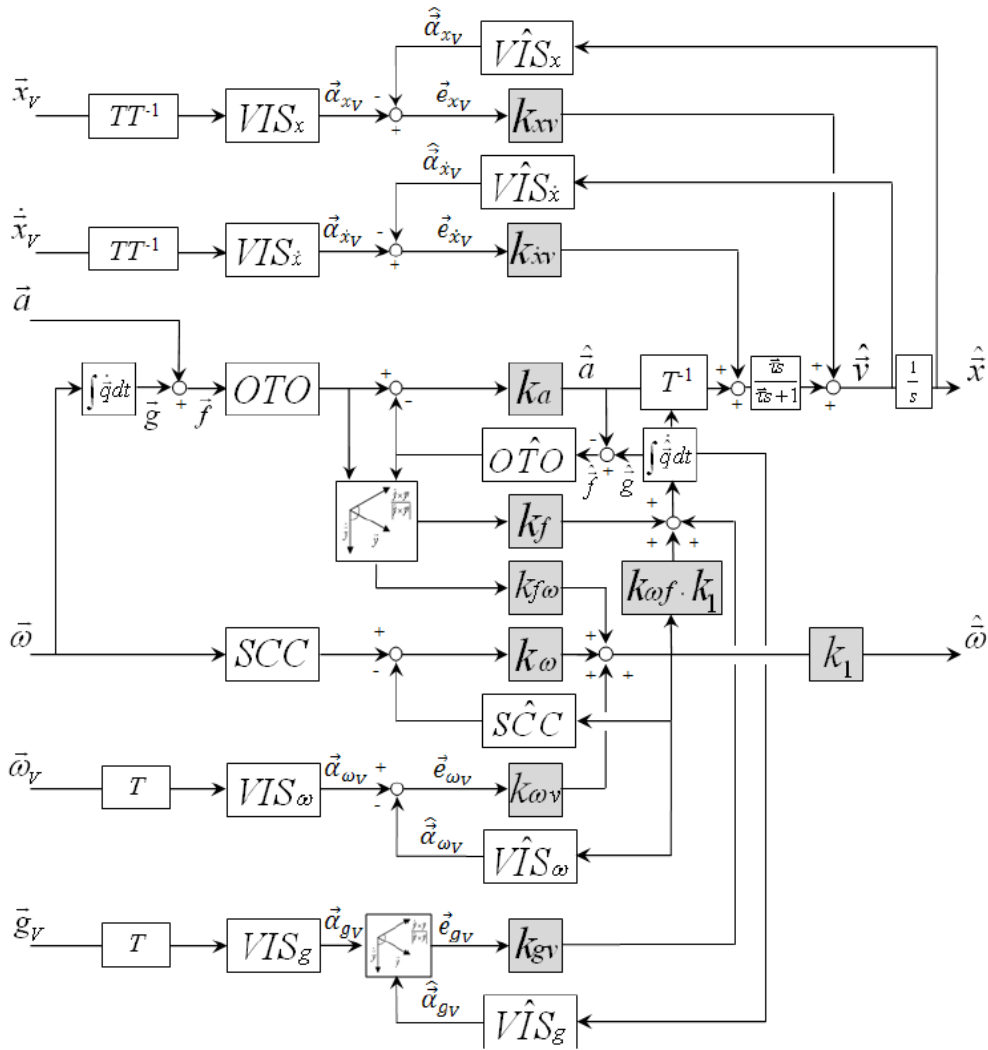
Figure 3-16. Visual – vestibular interaction model proposed by Newman (2009)

Basically, for the vestibular model, the mathematical was the same with the model proposed by Merfeld and Zupan. However, in this model the static and dynamic visual are added. In their model, the static visual position ($\vec{x}_v$), gravity ($\vec{g}_v$), dynamic visual velocity ($\dot{\vec{x}}_v$), and angular velocity ($\vec{\omega}_v$) were used as input for the model.

In this OKR model, for generating the visual sensory estimate $\vec{a}_{Vv}$, the visual ($\vec{V}_v$) is transformed through visual sensor (VIS$_V$). In this close loop, the expected visual sensory (($\hat{\vec{\alpha}}_{Vv}$) and the estimate ones are compared through C. The sensory conflict is present through parameter K$_v$.

Assumptions:

- The visual system is capable of extracting four visual cues from its environment
- Sensor dynamic

With the assumption that static and dynamic visual inputs are the visual system sensory dynamics.

For static Visual Cues

$$\frac{\vec{a}_{xV}}{\vec{x}_V} = VIS_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_{3 \times 3}$$

$$\frac{\vec{a}_{gV}}{\vec{g}_V} = VIS_g = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_{3 \times 3}$$

For dynamic Visual Cues

$$\frac{\vec{a}_{\dot{x}V}}{\dot{\vec{x}}_V} = VIS_{\dot{x}} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} = I_{3 \times 3}$$

$$\frac{\vec{a}_{\omega V}}{\vec{\omega}_V} = VIS_{\omega} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} = I_{3 \times 3}$$

. Sensor dynamic

$$\frac{\hat{\vec{a}}_{xV}}{\hat{\vec{x}}_V} = V\hat{I}S_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_{3 \times 3}$$

$$\frac{\hat{\vec{a}}_{gV}}{\hat{\vec{g}}_V} = V\hat{I}S_g = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_{3 \times 3}$$

$$\frac{\hat{\vec{\alpha}}_{\dot{x}V}}{\hat{\vec{x}}_V} = V\hat{I}S_{\dot{x}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_{3\times3}$$

$$\frac{\hat{\vec{\alpha}}_{\omega V}}{\hat{\vec{\omega}}_V} = V\hat{I}S_g = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_{3\times3}$$

- Error Calculations

$$\vec{e}_{xV} = \vec{\alpha}_{xV} - \hat{\vec{\alpha}}_{xV}$$

$$\vec{e}_{\dot{x}V} = \vec{\alpha}_{\dot{x}V} - \hat{\vec{\alpha}}_{\dot{x}V}$$

$$\vec{e}_{\omega V} = \vec{\alpha}_{\omega V} - \hat{\vec{\alpha}}_{\omega V}$$

In this function, the magnitude and directional component is required for gravitational error. The conflict of gravitational was calculated by:

$$\frac{\vec{e}_{gV}}{|\vec{e}_{gV}|} = \frac{\vec{\alpha}_{gV} \times \hat{\vec{\alpha}}_{gV}}{\left|\vec{\alpha}_{gV} \times \hat{\vec{\alpha}}_{gV}\right|}$$

$$\left|\vec{e}_{gV}\right| = cos^{-1}\left(\frac{\vec{\alpha}_{gV}}{\left|\vec{\alpha}_{gV}\right|} \times \frac{\hat{\vec{\alpha}}_{gV}}{\left|\hat{\vec{\alpha}}_{gV}\right|}\right)$$

This developed OKR model works by keeping the model structure and notation consistent with VOR model proposed by Merfeld, therefore the combination of VOR and OKR can be applied in a similar way with this method.

The importance of the VOR – OKR interaction was previously pointed out by Land (2006). However, up until now, there is no research succeeding in combining VOR and OKR to simulate eye movement not only for daily life but also while driving.

Since the visual information is important for driving as discussed above, we have to consider the OKR effect on the eye movement simulation.

On the other hand, to elucidate general mechanisms of the sensory motor learning, the interaction of the VOR and OKR was investigated by several researchers such as Masao Ito (1982, 1998), Mitsuo Kawato group (1992, 1998, 1999, 2000, 2001). In their research, with the main purpose to improve the cerebellar learning model, they found out that the cerebellum serves are an important function in the regulation of smooth eye movement. However, within this study, we are not considering about the smooth pursuit eye movement.

3.6. Final Common path

Because we're are only considered with the head and eye movements in the vertical direction, the two parameters for the horizontal gain (p_{kshor} and p_{krhor}) remained constant.

The output of VOR model is the angular velocity of eye ball in three directions. However, it is difficult to integrate of the angular velocity because of the gaze direction (Robinson 1981). Therefore, after calculating the eye movement, the final common path proposed by (Robinson 1981) was applied. In this part, two parameters (k_i, k_p) were used, based on the different types of the muscle fibers present in muscles of the eye (Figure 3-17).
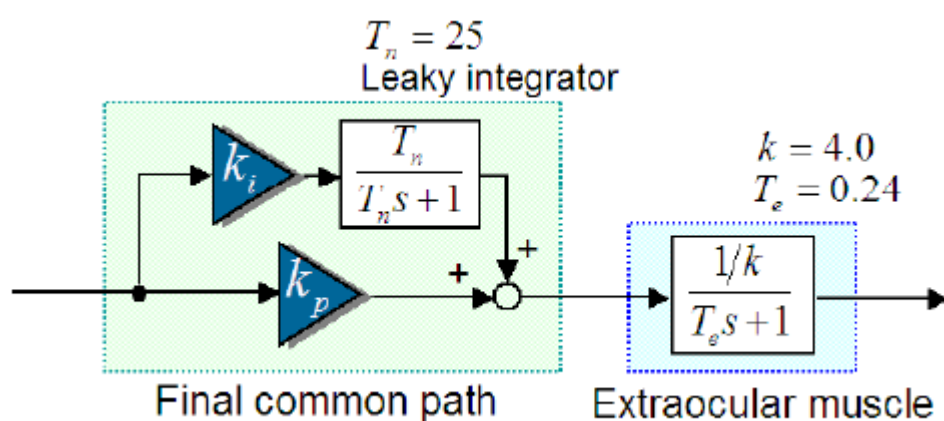
Figure 3-17. Visual target positions

CHAPTER 4:   PARAMETER IDENTIFICATION

4.1.   Introduction

As presented in Chapter 2, the VOR model had been proposed by several researchers and applied in various applications. In this research, with main purpose to simulate eye movement which can deal with the interaction between the otolith and the semicircular canal, the VOR model proposed by Merfeld and Zupan (2002) was used. Furthermore, the final common path proposed by Robinson was added to convert eye movement through eye muscle to get the final eye movement.
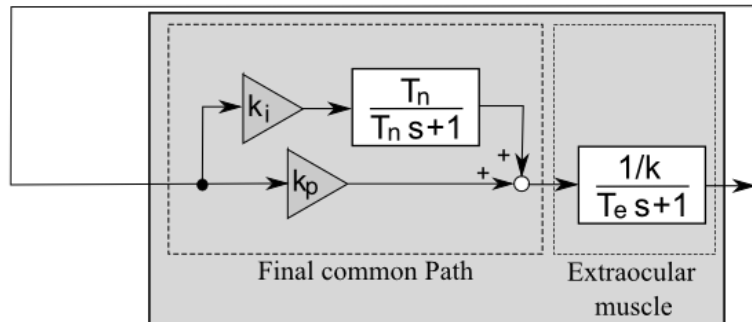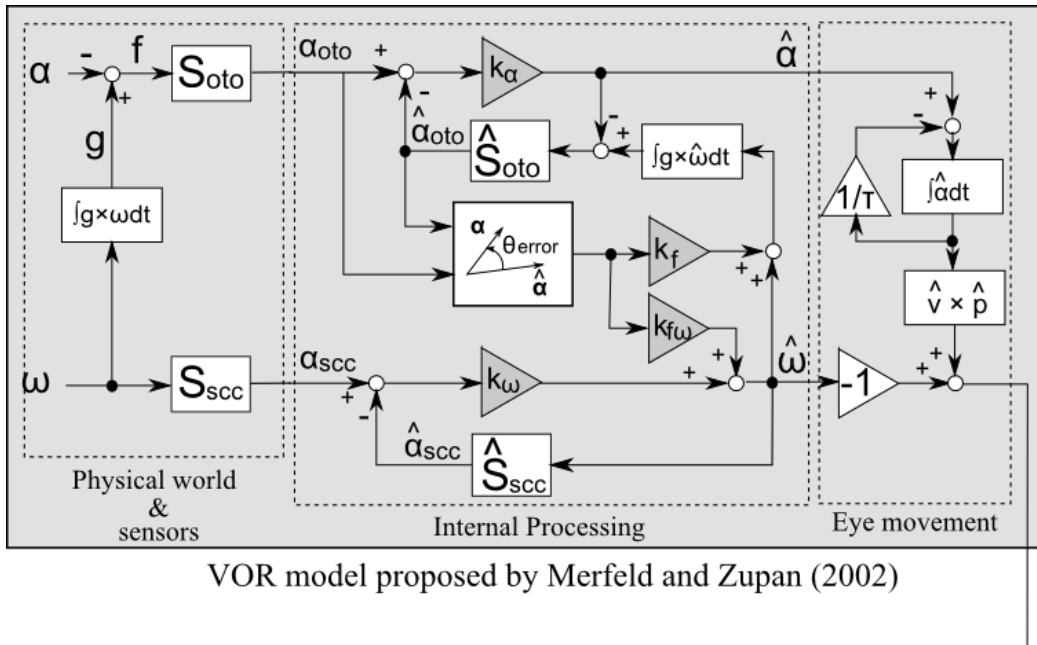
Figure 4-1. VOR model proposed by Merfeld and Zupan (2002) and Final common path part proposed by Robinson (1981)

In the VOR model, three parts of spatial orientation are shown: physical world & sensors, internal processing, and eye movement part. The linear acceleration and angular velocity of head movement are input of the VOR model. In this model, the resultant error signals are weighted with four free parameter (k_α, k_f, $k_{f\omega}$, and k_ω).

The main idea to create four parameters is to minimize the sensory conflict error (Merfeld et al. 1993). The parameter k_α, which calls the linear acceleration feedback gain, to feed the accelerator back to the central estimator by comparing the differences between actual and expected otolith signals. The parameter k_f, which is the GIF feedback, that scales the GIF rotation error to feed it back to the central estimator for the direction of gravity. It means that it weighted the difference between the direction of actual and expected otolith cues, while the remaining feedback gain ($k_{f\omega}$) is weighted the rotation of the gravireceptor cues and used to adjust the Observer's estimated of angular velocity. In other mission, the parameter k_ω is the angular velocity feedback gain, which corresponded to the slow phase velocity of VOR.

On the other hand, four parameter (k_{ih}, k_{iv}, k_{ph}, and k_{pv}) are contained in final common path part proposed by Robinson (1981).

In total, the model contained eight parameters. Each of them were had difference purpose which can reflect the individual characteristic. Therefore, eight parameters had to identify by each individual.

4.2. Literature reviews

By adjusting four parameters, this model was able to simulate eye movement based on head movement. In the past, there was several researchers applied this model to validate and extend the model such as Haslwanter et al. (2000), Merfeld and Zupan (2002), Vingerhoets et al. (2006, 2007), and so on.

In 1993, based on the experiment to minimize the sensory conflict errors, Merfeld at el found out the value of each parameter (Merfeld et al. 1993). In that experiment, by using the monkey responses, each parameter was fix at the difference value to remain the stable and keep signal in the central estimate.

Table 4-1. Parameters for VOR model

	Subjects	Method	Parameter Values			
			k_α	k_f	$k_{f\omega}$	k_ω
Merfeld et al. (1993)	Monkey	variable step algorithm	-0.9	2	20	3
Haslwanter et al. (2000)	Human	ex-plicit Runge-Kutta	-1	10	1	1
Merfeld et al (2002)	Human	Unknown	-2	2	2	3
Vingerhoets et al. (2006)	Human	Unknown	-4	2	8	8
Vingerhoets et al. (2007)	Human	Unknown	-4	4	8	8
Obinata et al.						

In 2000, Haslwanter et al. validated the VOR model in three dimensional eye movement responses to off-vertical axis rotations in humans. In their study, the variable step algorithm ode45, which based on an ex-plicit Runge-Kutta formula (Dormand-Prince pair) was used to find out the value of each parameter (Haslwanter et al. 2000). In this function, initial step size was set to 1.0×10^{-10} s, and the maximum step size was set to 0.1 s. The results of each parameter was shown in table 4-1.

Again, in 2003, Merfeld and his team applied the VOR model to see the tilt and translation responses. In that research, they tried to use this model for human and the parameter was re-identified. The new set of parameter was chosen based on the best performance (shown in table 4-1).

In 2006, 2007, Vingerhoets et al. also used the VOR model to see the illusory translation perception during off-vertical axis rotation (Vingerhoets 2006) (Vingerhoets et al. 2007). For the better egomotion perception, they change the parameter and found out the better ones (table 4-1).

After that, Obinata group applied the VOR model to evaluate driver mental while driving by comparing the eye movement simulation and measurement (Obinata & Tokuda 2008) (Usui et al. 2007) (Obinata et al. 2009) (Obinata et al. 2010). Inside of their works, the methodology for identifying parameter was improved by using hybrid genetic algorithm. However, the time for identifying still low (It took around

30 minutes to identify parameter for one individual) and that method still cannot applicable in case of changing gaze.

On the other hand, for parameter identification, there are several methods to find out the good parameters for each model such as Brute Force search, Nelder-Mead simplex, Trust region method, Gauss-Newton (Munster 2009), and so on. One of the successful methods is a Genetic algorithm (GA) which is founded on Darwinian evolutionary principles – mechanics of natural genetics (Goldberg n.d.). This method has been applied to a variety of areas especially for parameter estimation (Pearl 2001), (Wang et al. 2004), (Petcu & Leonida-dragomir 2010), (El-mihoub et al. 2006). The GA is suitable for optimization of non-linear problem by finding out the global optimal solution bases on natural selection and genetics.

Koljonen and Alander presented the effects of population size and the relative elitism on optimization speed and reliability of genetic algorithms (Koljonen & Alander 2006). They showed that the initial parameters had a strong effect on the optimization speed and reliability. Kuczapski and Micea showed a method to enhance GA by generating near optimal initial populations (Kuczapski et al. 2010).

4.3. Methodology

This chapter shows a new generation by using GA method and MATLAB (graphical user interface) with main ideal to make this model can applicable with gaze change by increasing the reliability and exact ability. To enhance the VOR parameters, we apply the generating near optimal initial population and change the fitness function. And then, we test this model in case of vibration and changing gaze to see the adaptation of the model by comparing the simulation and measurement eye movement. This is the importance step to simulation eye movement while driving with voluntary eye movement.

4.3.1. Experimental setup

Twelve subjects participated in the measurement experiments. The experiments were approved by the Nagoya University's Institute of Innovation for Future Society Ethical Review Board. All subjects were provided with explanations regarding the experimental procedure and gave their written informed consent.

The overview of experiment is shown in Figure 4-4. The motion capture (Optitrack Prime 17W) was installed with six cameras around an automobile seat with a caster placed on the guide rail. The seat can be moved by a lever by another person behind shown in Figure 4-4. The cameras capture the motion of the subject's head and the seat. In addition, T.K.K.2930a (Takei Scientific Instruments Co., Ltd.) was used for measure eye movement by limbus tracking method.

(a) Head   (b) Eyeball
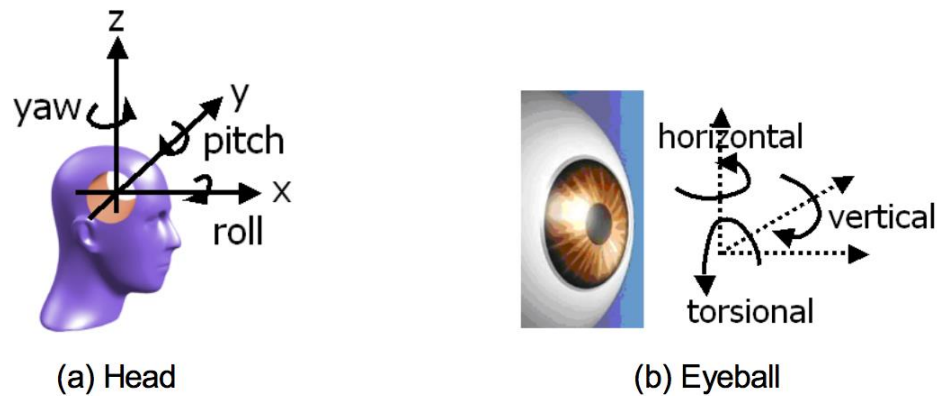
Figure 4-2. The coordinate system in our experiment

· Device information

- Optitrack Prime 17W

    Resolution: 1664 x 1088

    Pixel Size: 5.5 μm x 5.5 μm

    Frame Rate: 30-360 FPS

    Latency: 2.8 ms

    Shutter Speed 10 – 2500 μs

- Takei T.K.K 2930a

    Detection method: Infrared scleral reflection

    Irradiation peak wave length: 940

    Frequency: 9.6 kHz

Angle range: 20

Filter: Low pass filter

Output: 5V

ゴーグル部 　　　　　　　　　　　調整器部

Figure 4-3. Eye tracker

In this experiment, subjects who sit in the seat are given the pitching vibration while gazing at a target placed in front of the seat during that time. We measured the eyeball rotations, head movement and seat movement during that time. All data were imported to MATLAB with Data Acquisition Toolbox and processed.
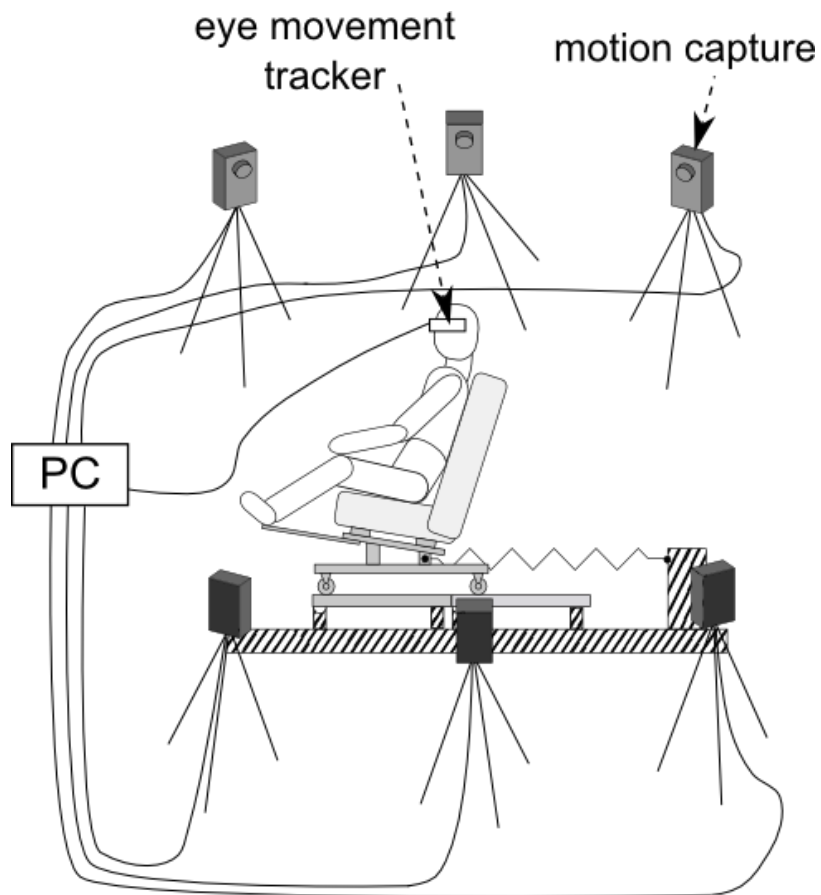
Figure 4-4. Overview of the experiment
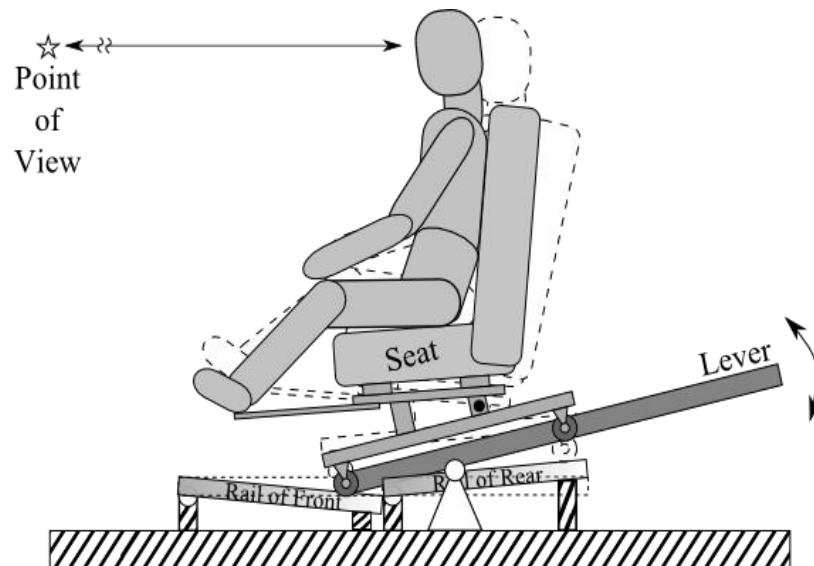
Figure 4-5. New parameter identification

The head movement is obtained by using an optical motion capture software (Motive software). Then, the data from Motive software live streaming markers are used to build the rigid body through Natnet SDK to MATLAB (Figure 4-6 and 4-7. On the other hand, the eye movement is collected by Takei Scientific Instruments 2930a. Because this device has analog output, a high-precision analog I/O terminal PCI (AOI-160802AY-USB, Interface Co. Ltd.) is used. By using Data Acquisition Toolbox, both data from the eye and head movements are synchronized and directly imported to MATLAB software. This synchronization is an important point to obtain better input values for the VOR model.
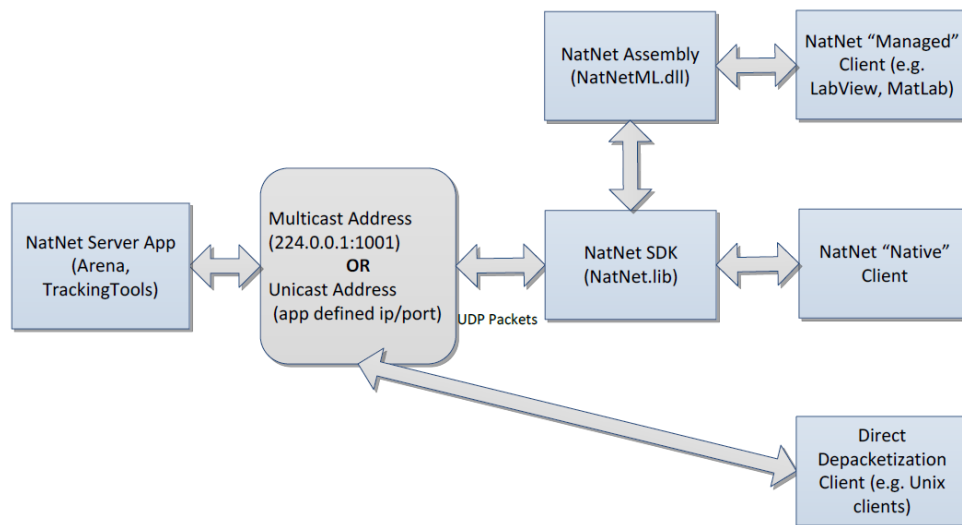
Figure 4-6. Natnet Component Overview
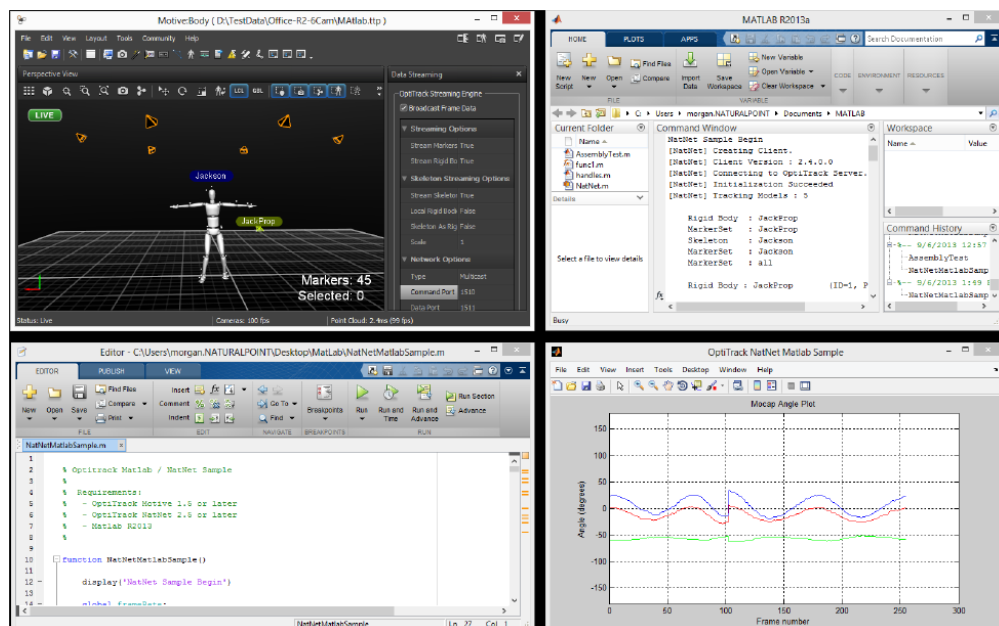
Figure 4-7. Real-time streaming Mocap data from Motive into MATLAB

After conducting the head and eye movement, the information was used as input of parameter identification of both new and old ones.

4.3.2. New parameter identification

The Genetic Algorithm (GA) is one of the optimization techniques by using fitness value. GA belongs to the larger class of evolutionary algorithms and its application in various fields such as bioinformatics, computer science, engineering chemistry, mathematics. Due to the aspects or the people who apply, GA can be used in different ways.

Figure 4-8 shows the comparison of the measurement and the simulation by applying original parameters proposed by Merfeld and Zupan. The result shows that there are big gaps between them. To deal with this problem, Genetic Algorithm (GA) will be applied with main purpose to find out better parameter for VOR models.
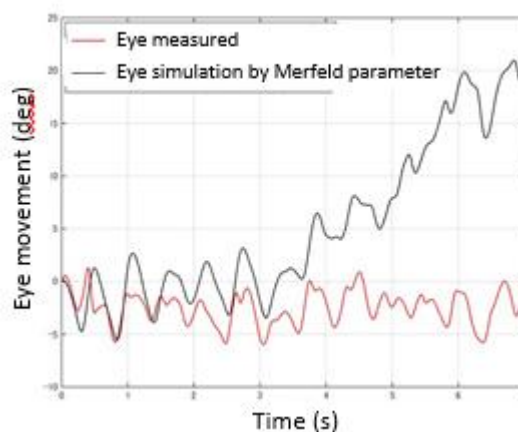
Figure 4-8. VOR model using Merfield and Zupan parameters
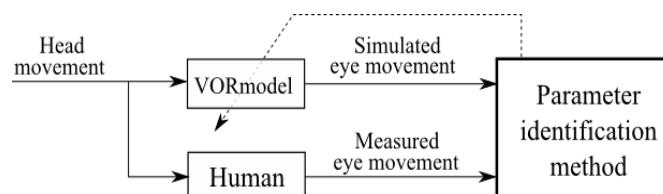
Figure 4-9. Data flow of the parameter identification

Figure 4-9 shows the flow of parameter identification. By comparing the simulated eye movement and the measured one, the parameter can be found out base on GA.

Based on the GA method of Beasley et al. (1993), GA provides a method to solve complex optimization problem with global search technique that searches multiple points. In this research, GA method is used for five steps (Figure 4-10): Initial population, evaluation, fitness value, reproduction cross-over and mutation, and stop – display result.

Initial population: The initial values of the estimate parameters are randomly assigned. On this research we use simple estimation base on fitness function value to find out the parameter have better results by comparing with the measurement.
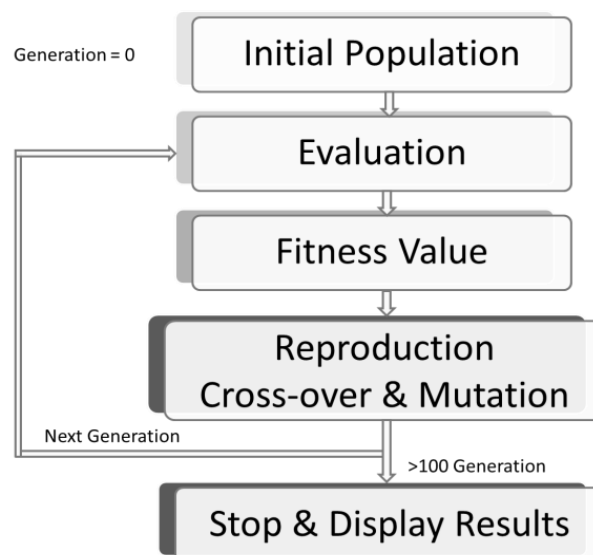
Figure 4-10. Genetic Algorithm

In their series of research, Obinata et al. used a hybrid – GA method for the VOR parameter identification (Usui et al. 2007), (Obinata & Tokuda 2008), (Omura et al. 2014). In these cases, 8 parameters from Merfeld and Robinson were identified at same time with initial value as Merfeld and Zupan parameters. However, due to the big range of each parameter, the result after 100 generations still had a small gap with the measurement. Based on this research, we found out the range of each parameter and ran a simple estimation. The results of estimation were used as the initial value for this time. The parameter also divided into two sets for estimation: the

first 4 parameters are from the VOR model proposed by Merfeld and the second 4 parameters are in the final common path proposed by Robinson.

Evaluation: By using MATLAB/SIMULINK, the VOR model was created based on the study by Merfeld and Zupan. The input signal was the head movement; with initial parameters from Merfeld, the output from the VOR model was compared with the measured eye movement.

Fitness value: In this research, we used fitness function of GA combine with mean square error. The duration of the mean square error was 6 seconds. The equation shows below:

$$\text{MSE} = 1/n \left(\Sigma \ (\text{eye simulation}_i - \text{eye measurement}_i)^2 \right)$$

Cross-over and mutation: this step is for preparing the next generation that selects genes from parent chromosomes and creates a new offspring. Then, mutation randomly changes the new offspring.

After 100 generations, the program stops and chooses the best result as a minimum of fitness value as well as showing it in the designing figure.

4.4. Results of parameter identification

4.4.1. Comparison the results from the VOR model using Merfeld and GA parameters

The difference of the simulation by this method and the measurement is shown as the value of mean square error. Table 4-2 shows the value of mean square error of each subject.

In total 12 subjects, all of the results from this GA method show better performance compared with the VOR model using Merfeld's parameters. The minimum mean square error of this method is 6.54E-5 and the maximum is 4.40E-3. On the other hand, by applying Merfeld's parameters for each subjects, we found higher error in the results. The maximum of mean square error is 3.80; it is higher than GA method more than 14837 times. However, in some case, the parameters of Merfeld are also acceptable with mean square error around 1.12E-3. It means that the higher errors are not due to the model but the parameter identification. Each

individual has different parameters for the VOR model. To find out the parameters that can be acceptable for any case or the rules of changing parameters of person needs to make more experiments with larger subjects and different characteristics.

Table 4-2. Mean square error of Merfeld and GA method

Subjects	MSE of Merfeld	MSE of GA	Merfeld/GA
Subject 1	1.05E-01	3.04E-04	3.47E+02
Subject 2	1.24E+00	2.90E-03	4.28E+03
Subject 3	1.12E-03	8.40E-04	1.33E+00
Subject 4	3.80E+00	2.56E-04	1.48E+04
Subject 5	1.65E-01	1.58E-03	1.04E+02
Subject 6	3.68E-01	6.54E-05	5.62E+03
Subject 7	5.22E-03	1.40E-03	3.73E+00
Subject 8	3.19E-01	1.20E-03	2.66E+02
Subject 9	8.11E-02	1.30E-03	6.24E+01
Subject 10	5.89E-01	5.87E-04	1.00E+03
Subject 11	6.26E-01	2.86E-04	2.19E+03
Subject 12	4.33E-01	4.40E-03	9.85E+01

Table 4-3. Mean square error hybrid and genetic algorithm

Subjects	HGA	GA	HGA/GA
Subject 1	4.0E-04	3.0E-04	1.31
Subject 2	3.3E-03	2.9E-03	1.14
Subject 3	8.5E-04	8.4E-04	1.01
Subject 4	3.2E-04	2.6E-04	1.25
Subject 5	1.6E-03	1.6E-03	1.01
Subject 6	6.9E-05	6.5E-05	1.06
Subject 7	2.1E-02	1.4E-03	14.86
Subject 8	1.5E-03	1.2E-03	1.25
Subject 9	1.7E-03	1.3E-03	1.31
Subject 10	1.0E-03	5.9E-04	1.70
Subject 11	2.9E-04	2.9E-04	1.01
Subject 12	2.0E-02	4.4E-03	4.43

Table 4-3 shows the comparison of the previous method that uses the hybrid GA with Merfeld and Zupan parameters as the initial values and this new GA method with simple estimation as the initial. The result of the new method shows better performance. In some cases, two methods present the same mean square error. In other cases, however, the new method shows much better results such as Subject 12 and 7 (4 times and 14 times, respectively). Figure 4-11 presents the measurement and simulation of two subjects (the left side is the vertical and the right side is the horizontal eye movement) from the VOR model using both parameters.
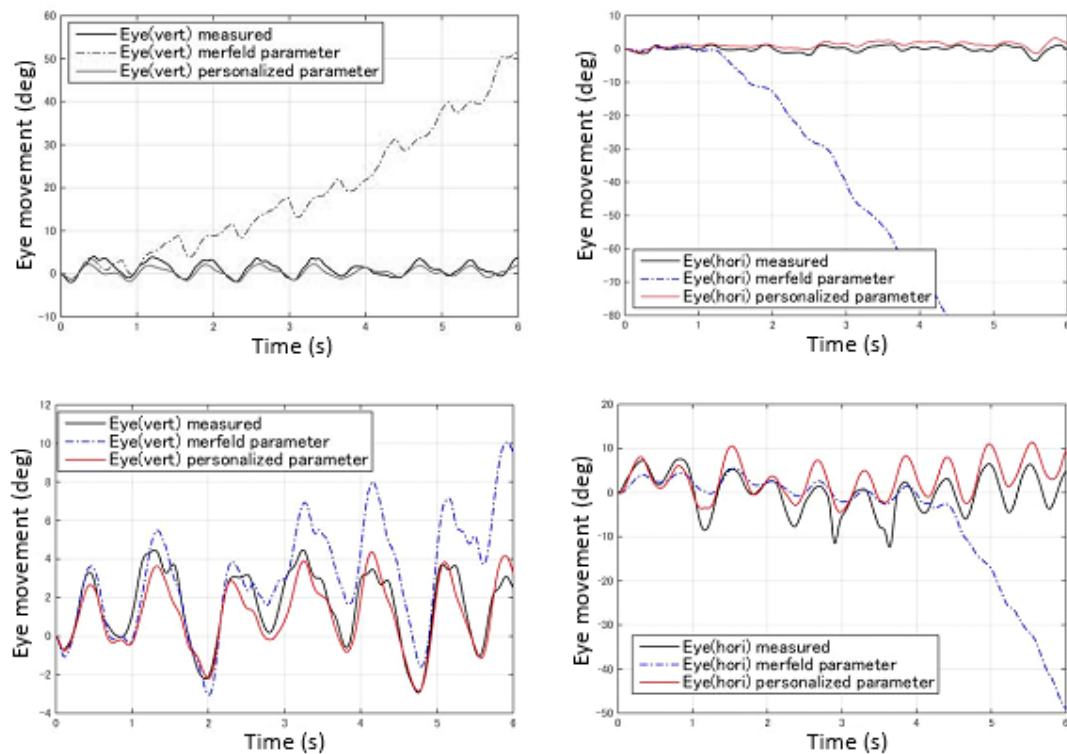
Figure 4-11. Result of VOR model

As same with MSE error, the result for running the VOR model using GA (personal) method show better performance compared with using Merfeld parameters. Both trend and value of the result using new method to identify parameter are almost same as the measurement.

4.4.2. Parameter for each subject using GA method

Table 4-4 shows the parameters of each subject. In total, we conducted 12 experiments with 12 different people. The parameters of each person are different,

which may represent the individual characteristics. The range of each parameter is based on choosing the initial of GA method.

All parameters have positive number except k_a. The minimum of k_a is around -13. On the other hand, other parameters are positive and maximum around 8. This is also a suggestion for other researches want to apply GA to identify parameter for VOR model can be easy to choose the initial parameters.

In the experiment, we tried to shake the chair only in pitch. Besides that, the people who shook the chair tried to make the frequency and amplitude as the same with all subjects. However, it was very difficult to keep the same frequency and amplitude by hand and thus, the input had some errors, which would also be the main reason for some bad parameters.

Table 4-4. Parameter of each subject

Parameters	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
ka	-6.4	-12.7	-12.7	-12.7	-9.4	-9.4	-12.7	-7.7	-7	-9.8	-6.4	-11.8
kf	0.1	0.1	0.1	0.1	0.3	0.4	6.3	0.4	0.1	0.1	0.1	0.1
kfw	4.9	0.1	0.1	1.5	1.9	2.4	0.1	1.5	1.8	2	0.1	4.2
kw	6.3	3.2	3.2	2.2	2.9	3.2	5.9	2	6.4	2.7	4.8	2.6
kiv	0.5	1.6	1.2	0.8	0.8	0.5	0.5	0.1	0.1	0.7	0.8	1.2
kih	0.7	2	2.4	1.5	2.7	0.3	0	0.9	0.8	0	0	0
kpv	1.4	0.1	5.4	2.3	3.2	2.3	4.7	1.7	1.5	2.1	2.3	7.5
kph	3.1	2.8	5.2	0.8	4.7	6.1	2.5	4.3	4.8	6.3	3.1	0

Focusing more on the details about the identified parameters, the value of k_f of Subject 7 is 6.3, which is more than 10 times higher than others. By checking the input data, we found that there was a big error from the head and eye movement inputs. In the middle of the experiment, the subject moved his head and eye down and made the horizon of eye and head movement change suddenly (Figure 4-12) which is the main reason for increasing k_f. It also implies that k_f has strong effect on the horizontal eye movement.

In case of k_{fw}, Subject 1 and 12 have quite bigger values compared with others. The reason is that the values of vertical eye movement increased by the time. It may be the effect by the people who controlled the movement of the chair (Figure 4-13).
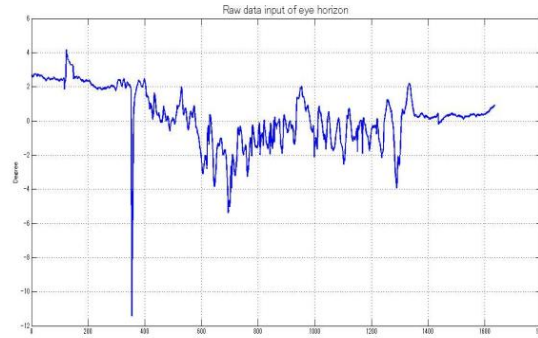
Figure 4-12. Raw data input of eye horizon
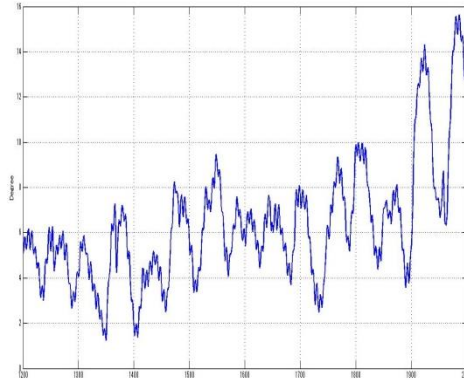
Figure 4-13. Raw data input of eye vertical

On the other hand, the four parameters (k_{ih}, k_{iv}, k_{pv}, and k_{ph}) from the Robinson model work mainly as gains for the signal output. k_{ph} and k_{ih} are gains of the horizontal eye movement. Those values of some subject are equal to zero because in this experiment, the experimenter shook the seat only in pitch. The error would occur when the seat is also moved in yaw.

4.5. MATLAB toolbox for identifying parameters

The MATLAB graphical user interface is used to create an application. The steps to build the program are shown in Figure 4-14. This toolbox consists of 3 steps. In the first step, input data which can support two kinds of hardware for each movement (head movement: Motive or Polhemus hardware; eye movement: Takei or Smart Eye hardware). In the next step, all input data can view in the figure which help users choose the area for identifying parameters (Figure 4-15).
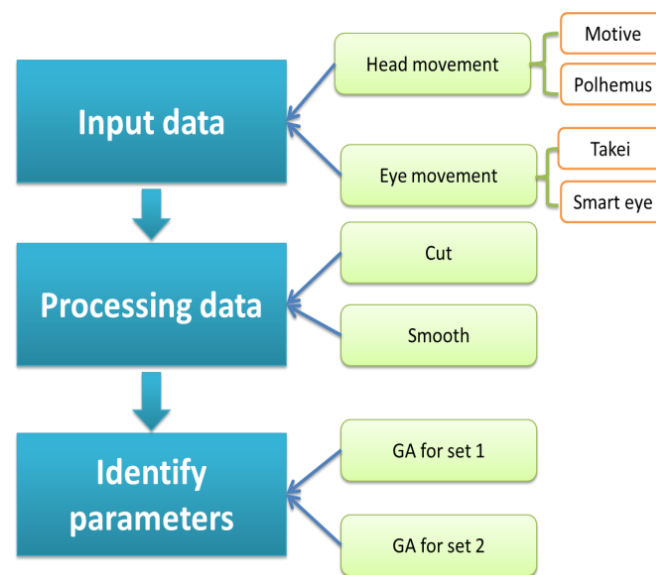
Figure 4-14. Step for identifying parameters

In the input and processing data steps, the tool shows with the menu bar that includes joint head marker (Figure 4-13). In this window, by choosing hardware, raw data of the eye and head movement are selected using a dialog box. The head and eye movements are shown in the Figure. By pressing on "View on Fig." button which helps people choose the best area to identify parameters. With one click on "Generate Data," two files consist of all information of the head and eye after cutting, transferring and smoothing are created as input of next step.
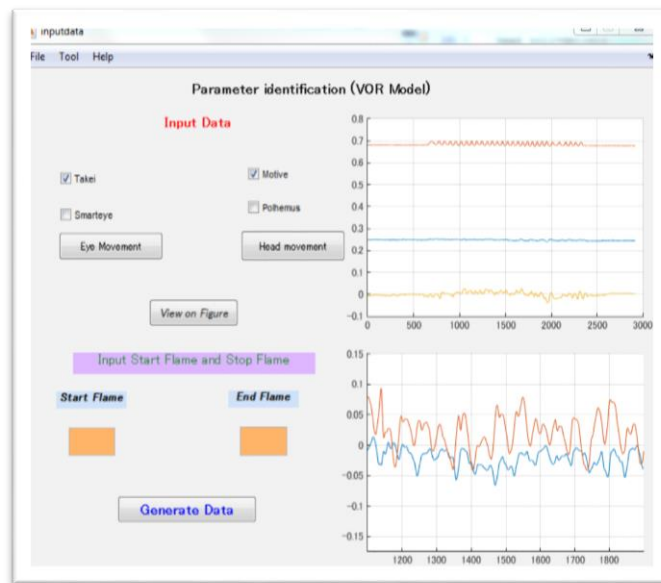
Figure 4-15. Input and processing data

In case of using old version of the motion capture which has only data for each marker, this tool supports to combine all markers become one which is used as the head movement input data.
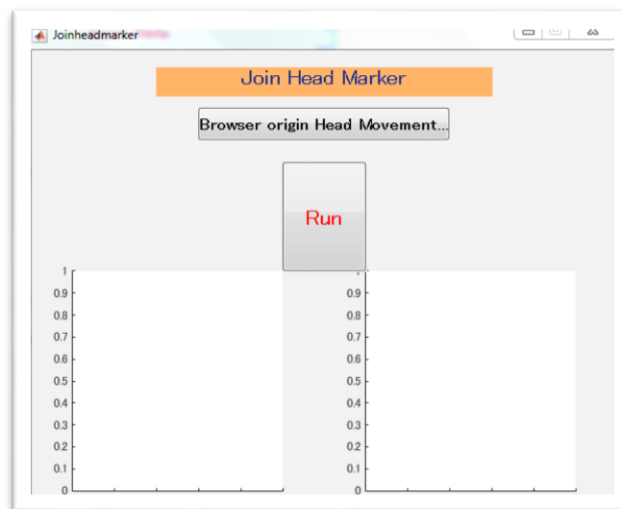
Figure 4-16. Join head marker

After generating data, the results of this tool are used for the parameter identification in the next step (Figure 4-16). All parameters after identification are shown in the windows and other information is saved in files under the same directory as the input data. Similarly, all of the parameters after identification are

also shown in the main program and saved in the same directory with the mean square error.
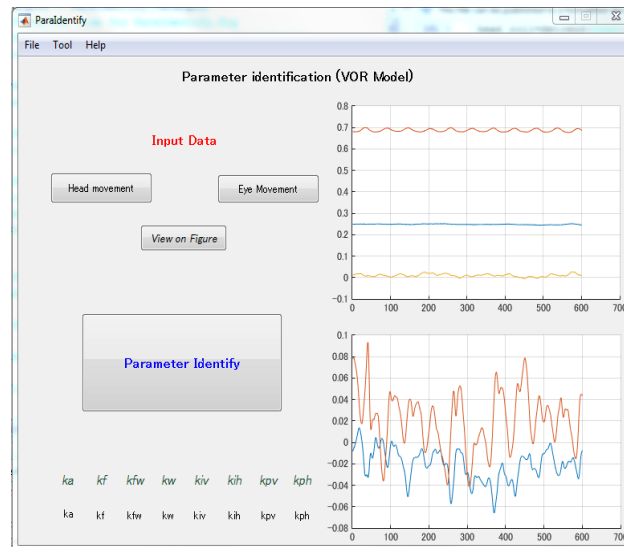
Figure 4-17. Parameter identification

4.6. Application with changing gaze

With main arm to test the identification toolbox. We conducted another experiment with CarSim (Mechanical Simulation Co.), Smart Eye pro (Smart Eye AB), and Fastrak electromagnetic tracker (Polhemus Inc.). The participant was asked to seat which vibration following the control of CarSim through MATLAB Simulink with fixed frequency in the vertical plane, and then move the eye following the instruction. The eye and head movement information was collected. The first ten seconds data in our experiment was used to identify the parameters and applied them to simulate the eye movement for the remainder of the experiment.

4.6.1. Setup experiment

We measured eye movements by using Smart Eye Pro (Smart Eye AB) with four cameras on the simulator. This equipment is noninvasive, simple to install, and provides data by using a camera recorder. To collect information on movements of the head, we used a Fastrak electromagnetic tracker (Polhemus Inc.).

Figure 4-18. Overview of the experimental setup

The same 12 subjects who participated in the previous experiment done this test for checking the parameter identification toolbox and then applied it in case changing gaze. During the parameter-identification phase, the participant was seated in the car simulator and looked straight ahead 10 seconds without changing their gaze. After that, the gaze will change following the instruction shown below.

Target order:

⓪ → ① → ⓪ → ② → ⓪ → ③ → ⓪ → ④ → ⓪ → ⑤ → ⓪ → ⑥ → ⓪ → ⑦ → ⓪

With time

10s → 5s → 5s → 5s → 5s → 5s → 5s → 5s → 5s → 5s → 5s → 5s → 5s → 5s → 10s

4.6.2. Parameter identification

The results of parameter identification following new method showed the good performance with well matching in both magnitude response and time response (Figure 4-19).
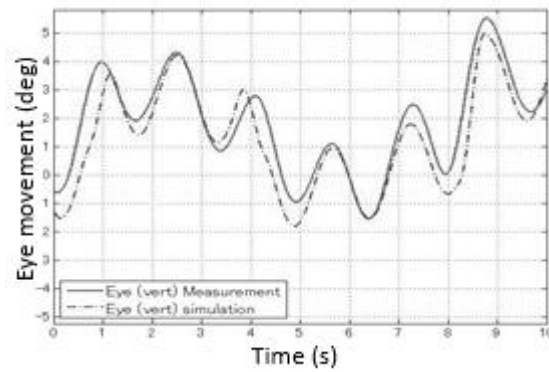
Figure 4-19. Eye movement in the vertical axis for subject 2

4.6.3. Eye movement simulation with changing gaze

The same with previous research, in the case of driver changing the gaze, the eye simulation still show good performance with low mean square error and matching well in both magnitude response and time response (Figure 4-20, Figure 4-21).
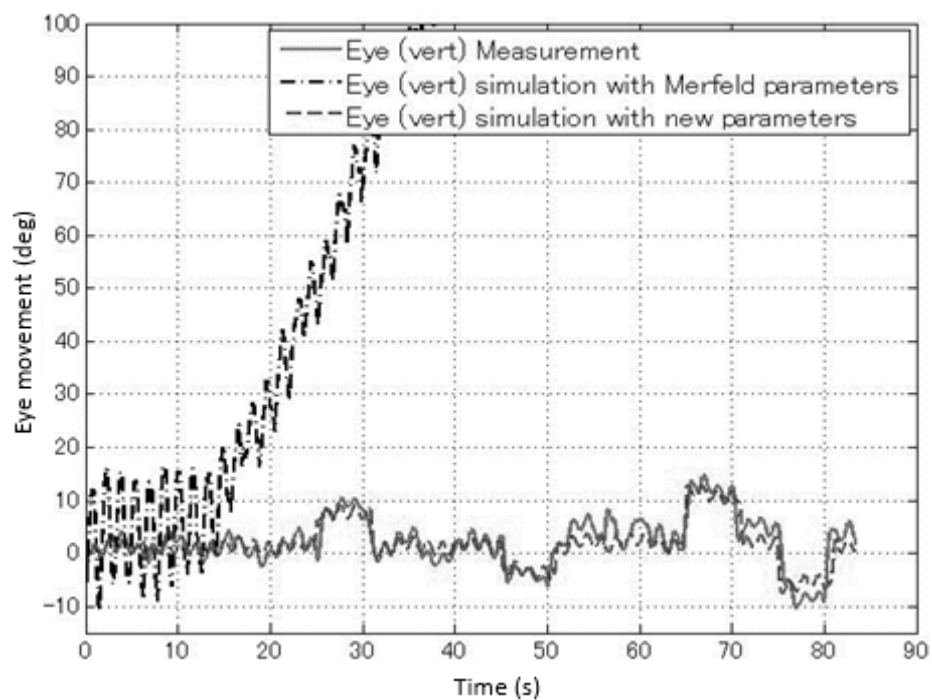
Figure 4-20. Eye movement in vertical axis of subject 2
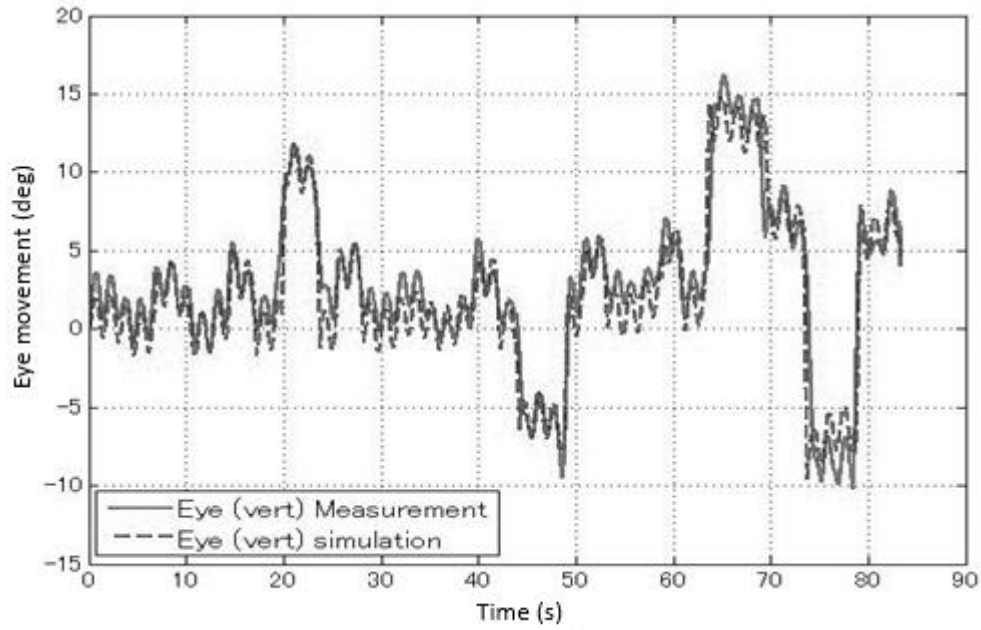
Figure 4-21. Eye movement in vertical axis of subject 8

On the other hand, the mean square error in this case was low with the maximum was 1.65E-03 rad and the minimum was 8.26E-04. The box plot of mean square error shown in Figure. 4-22.
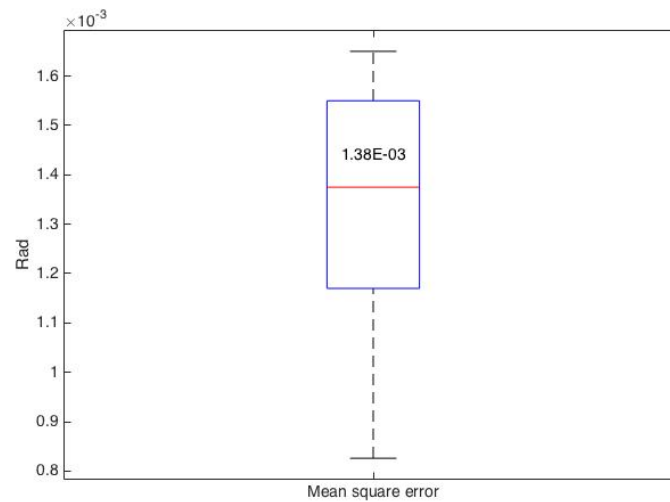
Figure 4-22. Boxplot of mean square error

This results confirm that by increasing of exact ability, here, the results of parameter identification can applicable while changing the gaze.

CHAPTER 5:   VESTIBULO-OCULAR REFLEX MODEL AND OPTOKINETICK RESPONSE MODEL

5.1.   Introduction

Driving requires a complex skill that involves with the vehicle itself (e.g., speed control), other road users (i.e., other vehicles, cyclists, and pedestrians), road infrastructure, surrounding environment, and so on. During driving a vehicle on a road, visual cues are the main source to supply information to the brain as a sensor which leads to decision making.

According to Henn et al (1974), Allum et al (1976), Robinson (1977, 1981), Waespe and Henn (1977a, b, 1978), and Schweigart & Mergner (1995), on the visual scene, the eye movement simulation requires to combine actions of the vestibulo-ocular reflex (VOR; eye stabilization in space) and the optokinetic reflex (OKR; eye stabilization on the visual scene).

The mathematical methodology for combining VOR and OKR was investigated from 1979 by Buettner and Buttner (1979) and Schmid et al (1979). By recording single neurons and trained to suppress nystagmus by visual fixation, they found out that the interaction between the vestibular and optokinetic should be done by creating a feedback loop, which is using visual information as a primary input. After that, there are several researchers was tried to find out the best way to adapt VOR with OKR model. For example, Masao Ito and his colleague (1982, 1984, 1985, 1991, 1997) done the experiment to introduce various models or VOR adoption and discussed about the connection between VOR and OKR with investigating of the behavior of Purkinje cells. However, most of their research focused on the horizontal direction (HVOR), which mostly work with smooth pursuit.

From 1995, Schweigart et al try to solve the interaction between VOR, OKR and smooth pursuit. In their study, the necessary of combining the VOR, OKR was confirmed especially during walking or driving a car. However, in their VOR model, the interaction between otoliths and semicircular canals was not investigated.

In this chapter, the effect of visual stimulus on involuntary eye movement during driving was investigated. On the other hand, we develop a model that consists of both vestibulo-ocular reflex (VOR) and optokinetic reflex (OKR) components to

simulate vertical eye movement. In this study, the VOR model proposed by Merfeld and Zupan, which deal with the interaction between otoliths and the semicircular canals, was applied.

5.2. Methodology

To simulate driver's eye movement even in the naturalistic traffic environment with optic flow of the visual scene and the driver's voluntary eye movement, the effect of optic flow from visual scene on eye simulation should be reduced by adding OKR model into VOR model. To confirm that, we conducted experiments in two cases: driving with/without visual stimulus by mean of a driving simulator. After that, the head movement was used to simulate eye movement by applying two kinds of models: only VOR model and both VOR and OKR models (Figure 5-1).
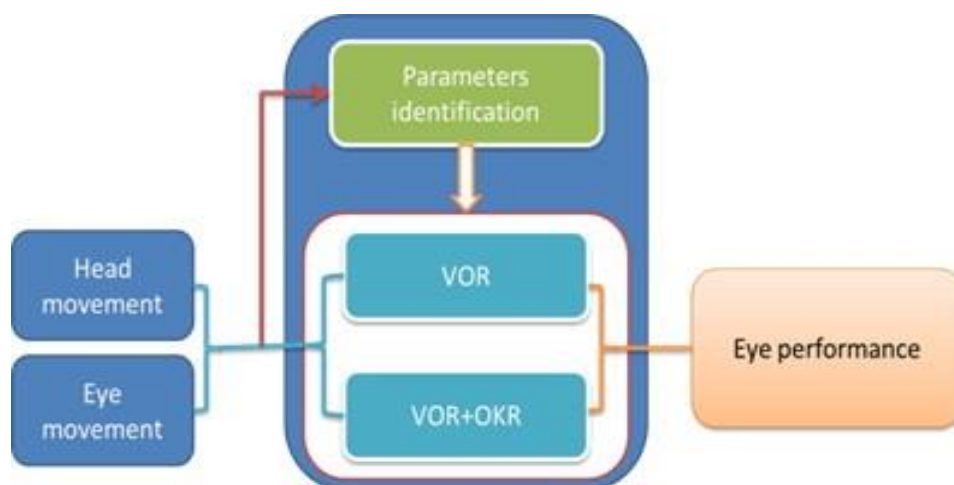
Figure 5-1. Overview of the research methodology

5.2.1. VOR+OKR model

The first proposal of combining VOR model and OKR model from Schweigart & Mergner. In their study, the interaction between VOR and OKR was presented by a feedback loop, which was used the head movement as a connection between VOR and OKR. The input of OKR model was the visual pattern, which is calculated from subject's head movements.

In a similar way with Newman (Newman 2009), Clark (Clark et al. 2015a) (Clark et al. 2015b), and Oman (Merfeld et al. 1993), one negative feedback loop was created which is important to stabilize the image on the retina and the VOR only as a useful addition which compensates for the limited bandwidth of the OKR during high frequency/velocity head rotations. Detail of the model is shown in Figure 5-2.

In case of driving, it is difficult to measure the input from vision because the target changes time by time. Therefore, we applied technique from Schweigart & Mergner (Schweigart & Mergner 1995) by using head movement in active condition. The visual information (VS) was calculated based on head movement (HS) following the function: $V_S = k*H_S$. The V_S was used as input of our OKR model.

The model proposed by Newman (2009) already established and successful applied to predict human perception and orientation. However, this is the first time to apply it to simulate eye movement for the driver.
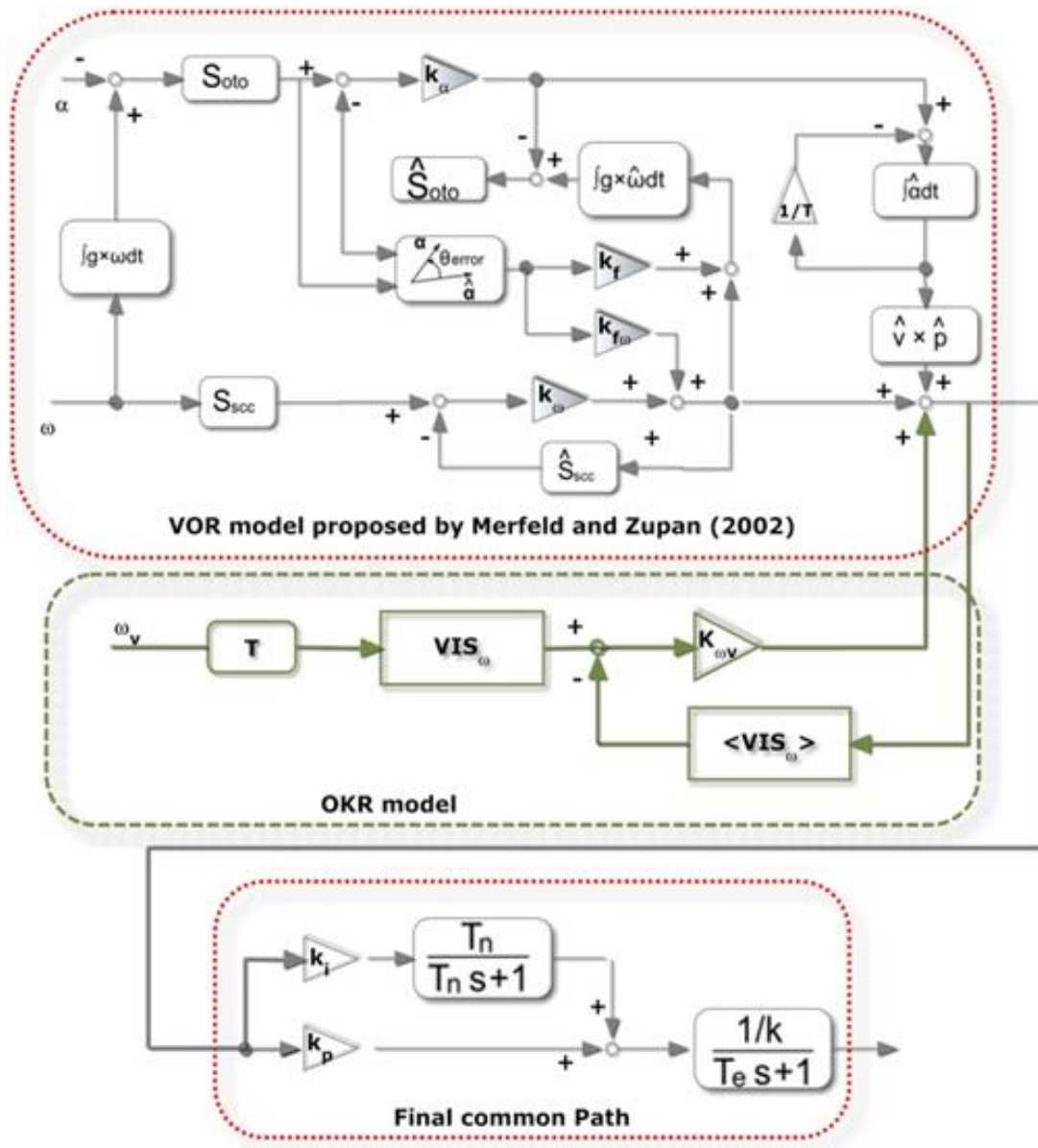
Figure 5-2. VOR+OKR model developed in this study

After that, a visual input is processed by visual sensor (VIS) to generate a visual sensory estimate. This estimate is compared to an expected visual sensory evaluated from internal model of visual sensor (<VIS>). And then the difference between visual sensory estimate and internal model of the visual sensor is weighted with a residual weighting parameter (K_V) and added to the rate of change of estimated state.

5.2.2. Experiment setup

In the experiment, a subject was asked to drive following the course on the seat of a driving simulator with six degrees of freedom. The simulator was controlled by CarSim (Mechanical Simulation Co.) which can simulate the dynamic behavior of a vehicle (figure 5-3). In these experiments, by using MATLAB Simulink (MathWorks) to control CarSim, the seat was moved with a fixed frequency in the vertical and horizontal plane.

In this study, 9 subjects who have driver license participated in the experiment. The experiments were approved by the Nagoya University's Institute of Innovation for Future Society Ethical Review Board. All subjects were provided with explanations regarding the experimental procedure and gave their written informed consent. The participant followed the course in two cases: driving without and with visual stimulus

Without VS   With VS

(trees around the road).

Figure 5-3. Overview of the experimental setup

The eye movement was collected by using Smart Eye Pro (Smart Eye AB) with four cameras on the simulator. This equipment is noninvasive, simple to install, and provides data by using a camera recorder. To collect information on movements of the head, we used a Fastrak electromagnetic tracker (Polhemus Inc.). In case of driving, the acceleration of head movement is the sum acceleration of the vehicle movement and the head movement.

Device information

- Smart Eye Pro

  o Sampling rate: 120 Hz
  o Gaze accuracy: 0.5 degree
  o Field of view: 900
  o Output: TCP/UPD/CAN
  o Data: Head orientation, eye position, eye gaze, pupil diameter, saccades, fixations, blink
  o Eyewear compatibility: Glasses, contact lenses, and sunglasses of non IR type
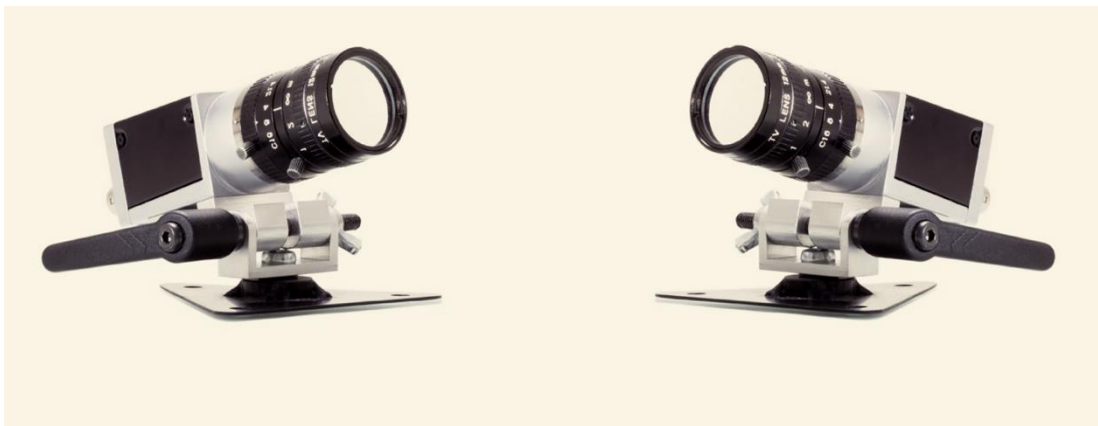
Figure 5-4. Smart Eye Pro

- Fastrak

  o Detection method: low frequency magnetic field vector
  o Data: three dimension
  o Range: 75cm
  o Accuracy: 0.8mm, 0.15 degree
  o Resolution: 0.005mm, 0.025 degree
  o Delay: 4 msec
  o Output: ASCII, BINARY
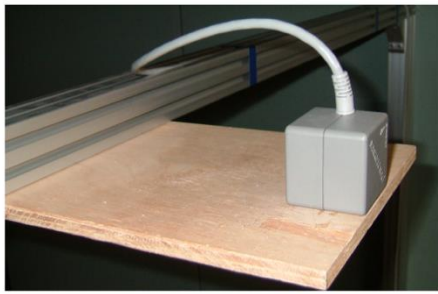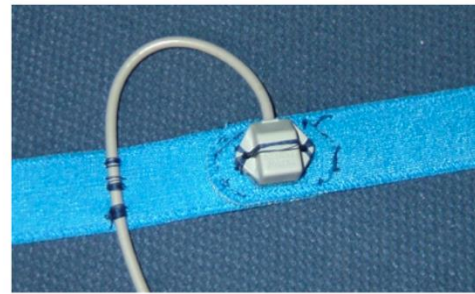
(a) Transmitter   (b) Reciever

Figure 5-5. Fastrak

·   Design course

We designed a course which includes straight parts, right and left turns, and narrow down. Trees were put around the road with density around 18 m per tree (Figure 5-6).
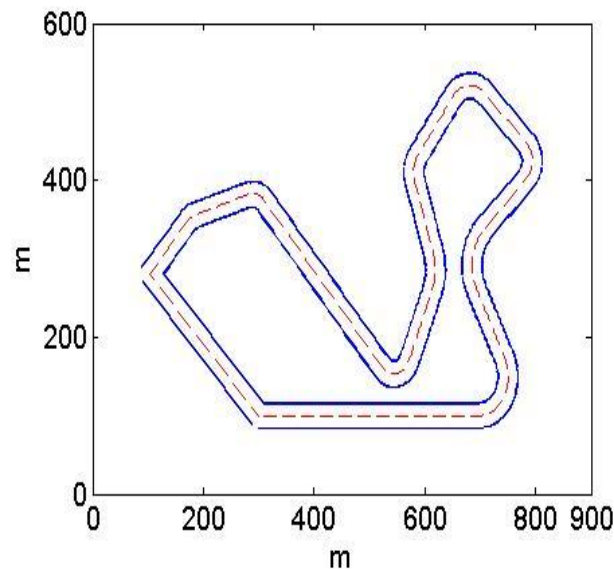
Figure 5-6. The course used in the experiment

·   Seat vibration

In order to create the movement of head and eye when driving, the seat was moved by the control of CarSim by using MATLAB Simulink. The seat was vibrated in two directions: vertical and horizontal. The detailed input for making the vibration is shown in Figure 5-7.
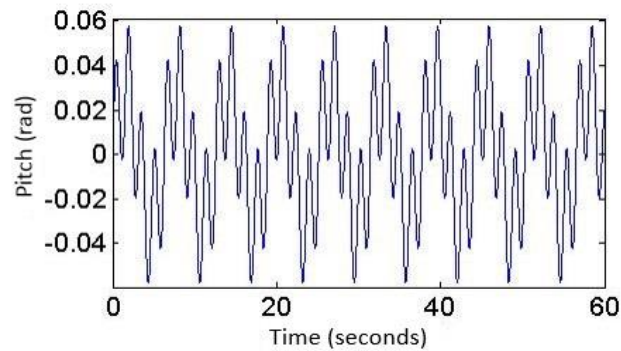
Figure 5-7. Input for seat movement

5.3. Results

Data from 9 subjects were collected. The subjects were asked to drive and follow the course at a speed between 40 and 60 km/h. The data of first 4 seconds when subjects drove go straight without visual stimulus was used to identify parameters using the developed parameter identification toolbox. The parameter identification was conducted in both models: VOR only and VOR+OKR, separately.

5.3.1. VOR model

· **Without visual stimulus (VS)**

By using VOR model, the results of simulation show good performance with low mean square error. Figure 5-8 confirmed that the simulation result was good matching in both time responses and frequency response.

Table 5-1 shows the mean square error (MSE) between simulation and measurement eye movement of each subjects in both direction: vertical and horizontal. The MSE on vertical direction and horizontal direction increased from 3.1E-04 to 4.3E-03 and from 1.7E-03 to 1.2E-02. The variability of MSE may depend on the driver history and individual characteristic. However, due to the limitation of the subject number, we can't see the effect of individual difference statistically in this present paper.
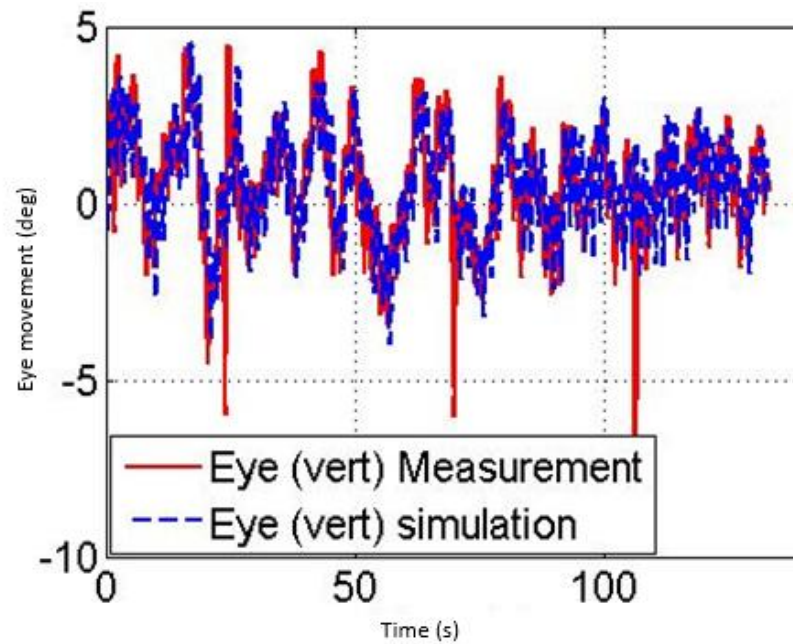
Figure 5-8. Eye movement in vertical by VOR without visual stimulus of Subject 1

Table 5-1. MSE of VOR model without VS of each subjects

Subjects	Experience	Vertical	Horizon	Total
S1	Regular**	3.1E-04	4.3E-03	4.6E-03
S2	Paper***	7.3E-04	2.6E-03	3.3E-03
S3	Regular	3.7E-04	6.6E-03	7.0E-03
S4	Regular	4.3E-03	3.5E-03	7.8E-03
S5	Paper	9.8E-04	3.0E-03	4.0E-03
S6	Regular	1.7E-03	4.0E-03	5.7E-03
S7	Regular	2.0E-03	1.2E-02	1.4E-02
S8	Paper	5.9E-04	1.7E-03	2.3E-03
S9	Regular	2.3E-03	3.3E-03	5.6E-03

* Unit: rad^2

** Regular: the person who drives most frequently

*** Paper: the person who just got driver license or rarely driving

· **With visual stimulus**

Base on the VOR model, the eye movement simulation with VS has larger difference than that without VS. The MSE with VS increased from 1.1 times to 2.6 times more compared with that without VS (table 5-2). This result means that the optic flow by VS increased the MSE by the VOR model. In next step, we added OKR model into VOR model to take the effect of optic flow into account in case of driving with VS.

Table 5-2. MSE of VOR model without VS and with VS of each subjects

Subjects	VOR Without VS [rad^2]	VOR With VS [rad^2]	Ratio With/Without
S1	4.6E-03	5.0E-03	1.1
S2	3.3E-03	3.6E-03	1.2
S3	7.0E-03	1.8E-02	2.6
S4	7.8E-03	1.3E-02	1.7
S5	4.0E-03	4.4E-03	1.1
S6	5.7E-03	6.2E-03	1.1
S7	1.4E-02	1.6E-02	1.1
S8	2.3E-03	3.4E-03	1.5
S9	5.6E-03	1.0E-02	1.8

In addition, when applied VOR model to simulated eye movement in case of with visual stimulus, the time response and magnitude response became miss-matching (figure 5-9).
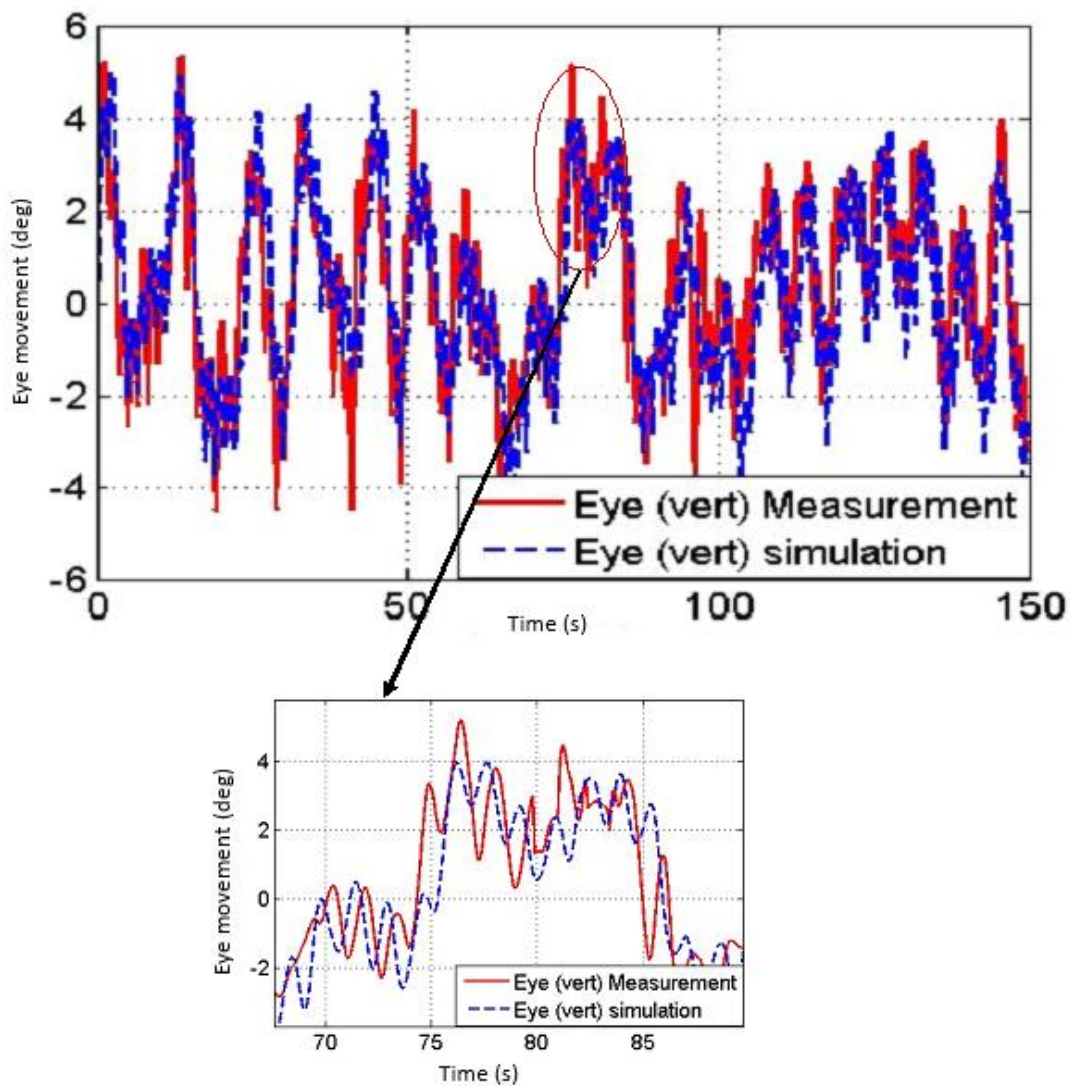
Figure 5-9. Eye movement in vertical by VOR with visual stimulus of Subject 1

5.3.2. VOR + OKR model

· **Without visual stimulus**

By the same token in VOR model without visual stimulus, VOR + OKR also showed very good performance with low MSE. The magnitude response and time response was good matching (figure 5-10).
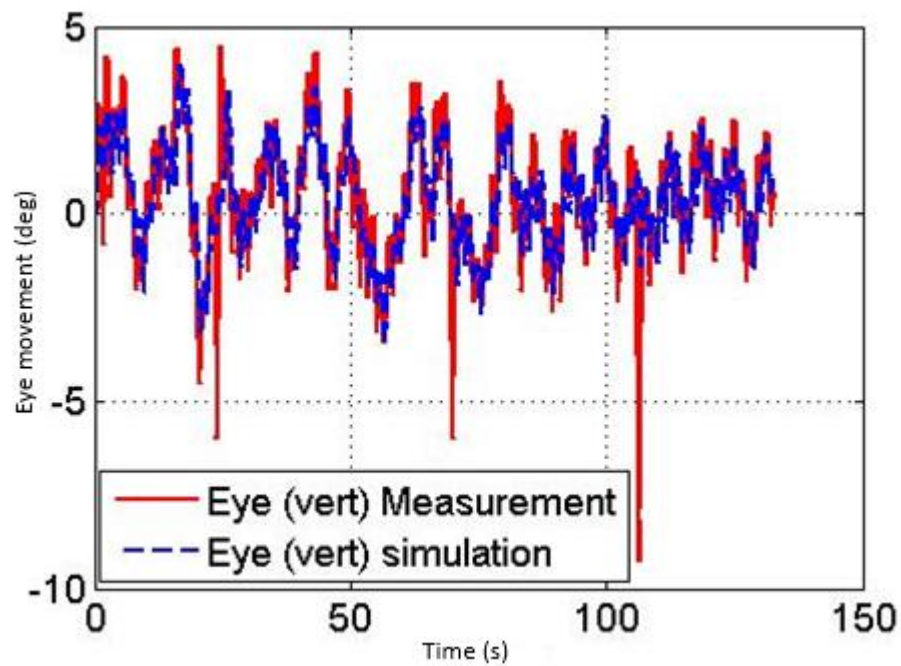
Figure 5-10. Eye movement in vertical by VOR+OKR without visual stimulus of Subject 1

Furthermore, the MSE of VOR+OKR model was even better than MSE of VOR model. As results shows in table 5-3, the MSE of VOR+OKR model was smaller than that of VOR model. The ratio of VOR+OKR/VOR model increased from 0.3 times to 1.0 times.

Table 5-3. MSE of VOR model and VOR+OKR model without VS of each subjects

Subjects	VOR Without VS $[rad^2]$	VOR+OKR Without VS $[rad^2]$	Ratio of (VOR+OKR)/VOR
S1	4.6E-03	3.3E-03	0.7
S2	3.3E-03	3.3E-03	1.0
S3	7.0E-03	2.4E-03	0.3
S4	7.8E-03	6.0E-03	0.8
S5	4.0E-03	2.5E-03	0.6
S6	5.7E-03	3.7E-03	0.7

S7	1.4E-02	8.8E-03	0.6
S8	2.3E-03	1.2E-03	0.5
S9	5.6E-03	3.6E-03	0.6

· **With visual stimulus**

Figure 5-11 shows the eye simulation and eye measurement in case of driving with VS. In contrast with VOR model in case of driving with VS, the results indicated that the time response and frequency response were good matching. Moreover, the results of VOR+OKR model still shown the same way with VOR model with higher MSE in case of with VS (Table 5-4).
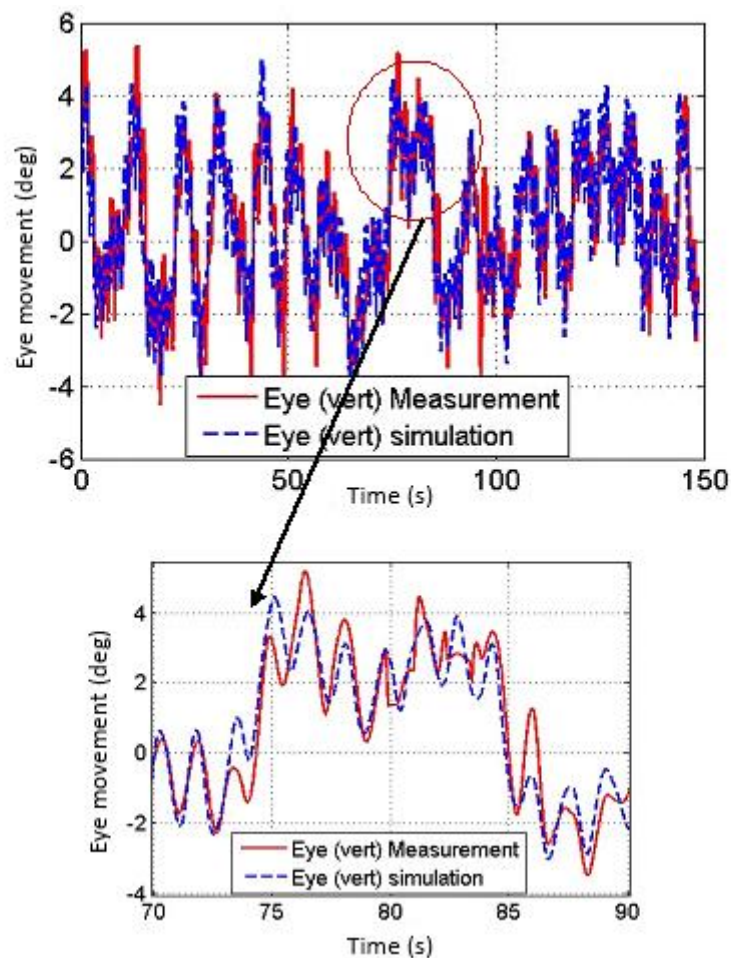
Figure 5-11. Eye movement in vertical by VOR+OKR with visual stimulus of Subject 1

Similar to the VOR model, the MSE of VOR+OKR model with VS was also bigger than without VS (table 5-4). The ratio between with and without VS increased from 1.1 to 1.6 times.

Table 5-4. MSE of VOR+OKR model with and without VS of each subjects

Subjects	VOR+OKR Without VS [rad^2]	VOR+OKR with VS [rad^2]	Ratio With/Without
S1	3.3E-03	3.7E-03	1.1
S2	3.3E-03	4.1E-03	1.2
S3	2.4E-03	3.1E-03	1.3
S4	6.0E-03	9.4E-03	1.6
S5	2.5E-03	3.9E-03	1.6
S6	3.7E-03	4.2E-03	1.1
S7	8.8E-03	9.7E-03	1.1
S8	1.2E-03	1.6E-03	1.4
S9	3.6E-03	5.3E-03	1.5

5.3.3. Effect of the OKR and the visual stimulus

Figure 5-12 shows the average MSE of VOR and VOR+OKR models in case of with and without VS. The VOR+OKR model shows better performance with lower MSE comparing with VOR model. The VOR+OKR model made the eye simulation became more precise with lower MSE even in case of with visual stimulus.

Moreover, we performed an analysis of variance (ANOVA) for 9 subjects in the presence and absence of visual stimulus, and with VOR or VOR+OKR model following null hypothesis.

- The results with and without visual stimulus are equal.

- The results of VOR model and VOR+OKR model are equal.
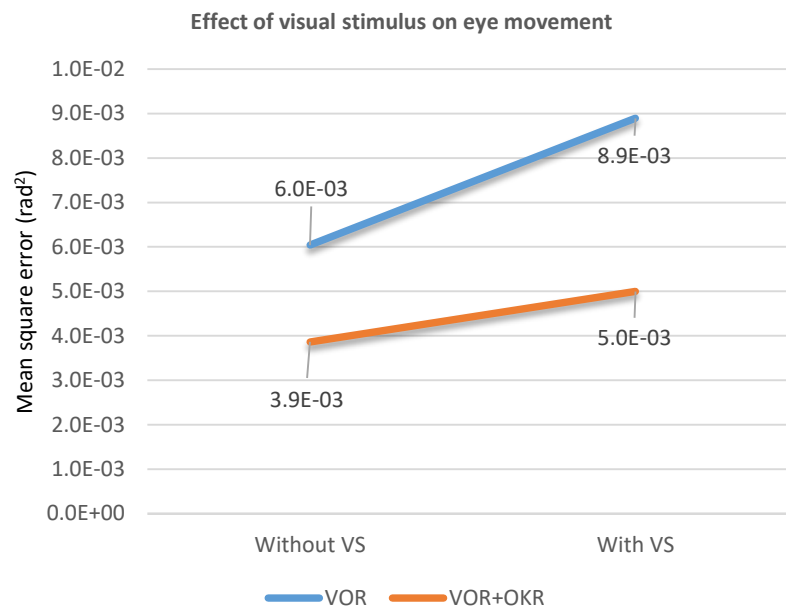
Figure 5-12. The average MSE of VOR and VOR+OKR model

The result shows in table 5-5

Table 5-5. ANOVA results

	df	Sum Sq	Mean Sq	F value	Pr(>F)
VS	1	3.5E-05	3.5E-05	2.47	0.126
Model	1	8.1E-05	8.1E-05	5.79	0.0221*
VS:Model	1	6.2E-06	6.2E-06	0.44	0.513
Residuals	22	4.5E-04	1.4E-05		
*: p < 0.05					

We found that the VOR model and VOR+OKR model was significantly different (F=5.79, p<0.05). Although there was tendency of the effects of VS and the interaction between the VS x Model, the ANOVA results indicated that the visual stimulus was not significant and there was no interaction between visual stimulus and VOR and VOR+OKR model. This may due to the limitation of the number of subjects (N=9). It once again confirmed that VOR+OKR show better performance comparing with VOR model.

CHAPTER 6:   EVALUATION OF DRIVER DISTRACTION USING EYE REFLEX MODEL

6.1.   Evaluating driver distraction with changing gaze

6.1.1.   Experimental setup

In the experiment, a subject was asked to sit on the seat of a driving simulator with six degrees of freedom. The driving simulator had a cylindrical 360° screen 6 m in diameter. The simulator was controlled by CarSim (Mechanical Simulation Co.) which can simulate the dynamic behavior of a vehicle (Figure 6-1). By using MATLAB Simulink (MathWorks) to control CarSim, the seat was moved with a fixed frequency in the vertical plane, as in previous experiments.

We measured eye movements by using Smart Eye Pro (Smart Eye AB) with four cameras on the simulator. This equipment is noninvasive, simple to install, and provides data by using a camera recorder. To collect information on movements of the head, we used a Fastrak electromagnetic tracker (Polhemus Inc.).

A total of 15 subjects who drive on a regular basis participated in the experiment to test the parameter-identification method. The experiments were approved by the Nagoya University's Institute of Innovation for Future Society Ethical Review Board. All subjects were provided with explanations regarding the experimental procedure and gave their written informed consent. During the parameter-identification phase, the participant was seated in the car simulator and looked straight ahead for 10 s without changing their gaze. The seat movements were controlled by CarSim and were identical for each individual.
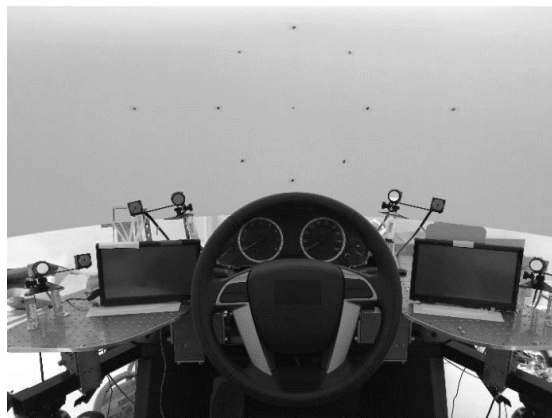
Figure 6-1. Overview of the experimental setup

Subsequently, we conducted an experiment to examine the effect of mental workload on eye movement. The gaze information was used to offset eye movement after simulating eye movement. The gaze movement was as shown below (Figure 6-2).
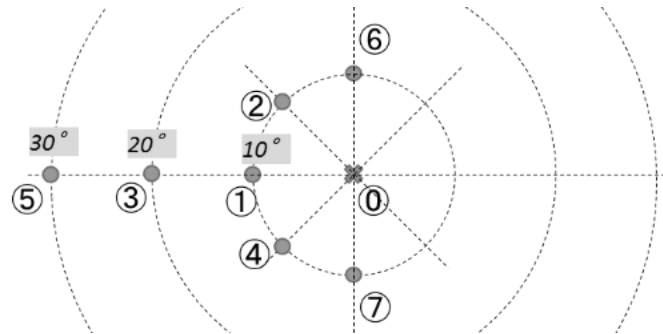
Figure 6-2. Visual target positions

Target order:

$$\textcircled{0} \rightarrow \textcircled{1} \rightarrow \textcircled{0} \rightarrow \textcircled{2} \rightarrow \textcircled{0} \rightarrow \textcircled{3} \rightarrow \textcircled{0} \rightarrow \textcircled{4} \rightarrow \textcircled{0} \rightarrow \textcircled{5} \rightarrow \textcircled{0} \rightarrow \textcircled{6} \rightarrow \textcircled{0} \rightarrow \textcircled{7} \rightarrow \textcircled{0}$$

With time

$$10s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 5s \rightarrow 10s$$

In this case, CarSim produced identical movements of the car seat in all the experiments, each consisting of two different sine waves. Subjects seated on the chair changed their gaze to comply with instructions.

An n-back task was used to evaluate distraction. In the n-back task, a series of one-digit numbers is presented verbally to the subject. The subject is then asked to answer by pressing a button on the steering wheel when the current number matches the number given n steps earlier in the sequence. In this study, n = 1 and the interval between two successive numbers was 2 s.

A total of 15 subjects participated (two trials per subject); the subjects had different individual characteristics.

6.1.3. Results and discussions

Figure 6-3 shows the original measurements and simulation results for Subject 2 in the absence of an additional mental workload (MWL) for a total of 83.8 seconds. The mean-square error for Subject 2 without an offset was 9.2E–03.
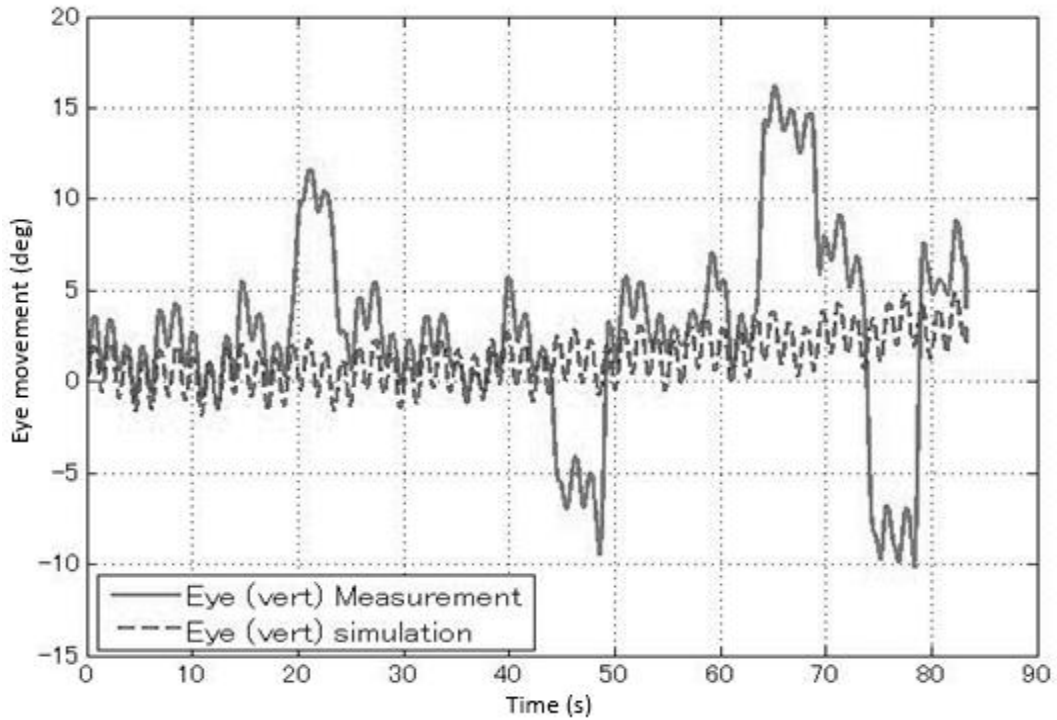
Figure 6-3. Simulated vertical eye movement without an offset

On the basis of the time required to change the gaze direction, we created an offset value at a given time point by means of the following equation:

$$\text{Offset (i) = average [measurement (start:stop)]} - \text{average[simulation(start:stop)]}$$

After incorporation of the offset (Figure 6-4), the mean-square value for Subject 2 fell to 4.25E–04.
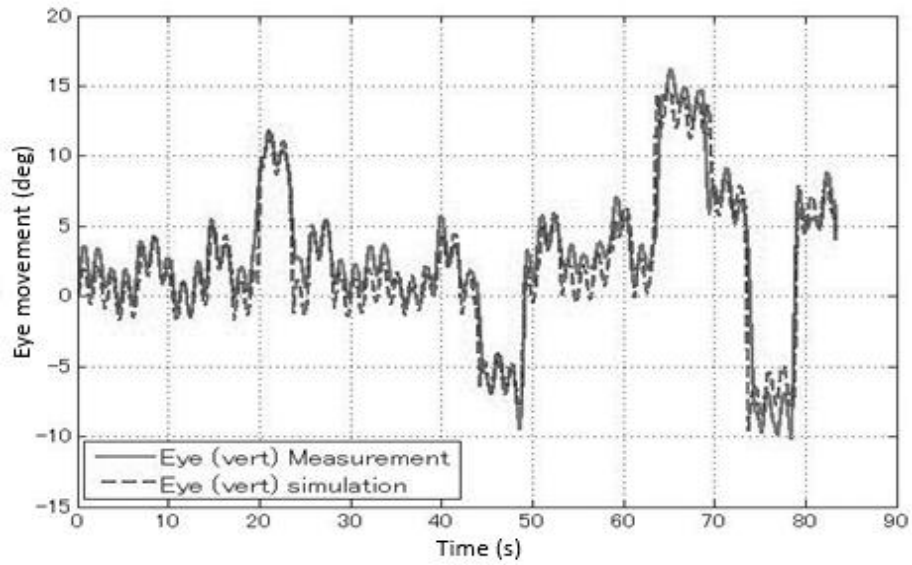
Figure 6-4. Vertical eye movement simulation with offset

When an n-back task with a 1 s interval was used, a large difference was observed between the case with an MWL and that with no MWL. The mean-square error without an offset increased 1.33 times to 0.0123. With an offset, it increased 2.83 times to 0.0012. Figure 6-5 shows details of the simulation and results of measurement for this case.
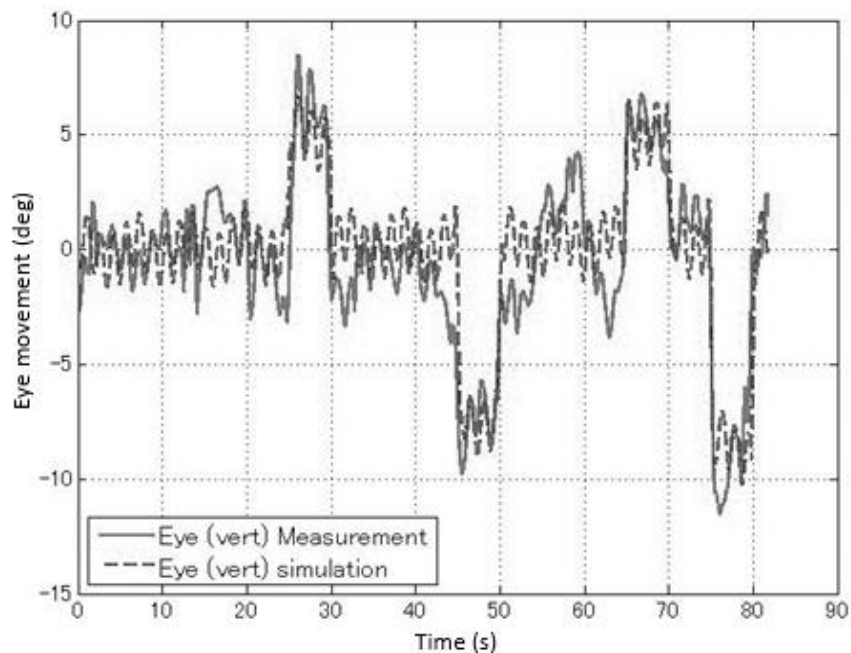
Figure 6-5. Vertical eye-movement simulation with a mental workload

With an MWL, the time and frequency response became mismatched. Consequently, the mean-square error increased compared with that in the absence of an MWL.

We conducted the same experiments for each participant with and without an MWL and we took the average of two trials for each subject; the details of the mean-square error are shown in Table 6-1.

Table 6-1. Mean-square error in the presence and absence of an MWL

Subject	No MWL		With MWL		Ratio	
	No offset	offset	No offset	offset	No offset	offset
1	9.00E–03	1.01E–03	9.25E–03	2.85E–03	1.03	2.81
2	4.65E–03	1.35E–03	9.50E–03	6.15E–03	2.04	4.56
3	5.45E–03	1.55E–03	7.70E–03	4.60E–03	1.41	2.97
4	6.25E–03	1.65E–03	1.09E–02	5.20E–03	1.74	3.15
5	6.10E–03	1.10E–03	7.10E–03	2.00E–03	1.16	1.82
6	6.30E–03	1.30E–03	9.30E–03	4.70E–03	1.48	3.62
7	4.30E–03	8.26E–04	4.70E–03	1.35E–03	1.09	1.63
8	4.30E–03	1.24E–03	5.60E–03	2.20E–03	1.30	1.77
9	4.70E–03	1.55E–03	6.60E–03	3.05E–03	1.40	1.97
10	3.50E–03	1.43E–03	5.70E–03	4.50E–03	1.63	3.15
11	4.55E–03	1.55E–03	4.95E–03	2.50E–03	1.09	1.61
12	3.95E–03	1.40E–03	5.40E–03	1.85E–03	1.37	1.32
13	7.30E–03	4.30E–03	1.25E–02	5.45E–03	1.71	1.27
14	6.00E–03	2.00E–03	1.03E–02	3.80E–03	1.71	1.90
15	3.40E–03	1.14E–03	5.60E–03	4.20E–03	1.65	3.68

Next, we performed an analysis of variance (ANOVA) for 30 trials of 15 subjects in the presence and absence of a mental workload, and with and without an offset with the following null hypothesis.

-        The results with and without an offset are equal.

-        The results in the presence and absence of a mental workload are equal.

-        The results of Trial 1 and Trial 2 are equal.

The result of the ANOVA is shown in Table 6-2.

Table 6-2. ANOVA results

Offset: a1: Without offset; a2: With offset

MWL: b1: No MWL; b2: With MWL

Trial: c1: Trial 1; c2: Trial 2

Table 6-2. ANOVA results

	Df	Mean Sq	F value	Pr(>F)	
Offset	1	4.73E−04	142	2.00E−16	***
MWL	1	1.36E−04	40.9	3.50E−09	***
Trial	1	2.1E−06	0.643	0.424	
Offset*MWL	1	1.4E−06	0.416	0.520	
MWL*Trial	1	7.60E−07	0.103	0.749	
Residuals	116	3.3E−06			
***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$					

As expected, the effects of the offset and MWL were statistically significant (F = 142, p < 0.001, and F = 40.9, p < 0.001, respectively). The mean-square error in the presence of an offset was significantly smaller than that in the absence of an offset, whereas that for no MWL was significantly smaller than that with a MWL. This shows that the method we have developed works well for evaluating MWL. There was no significant difference between the two trials and no interaction between the trial for MWL + offset and that with MWL only (p = 0.424 and 0.52, respectively). This shows that our method can be used to evaluate driver distraction on the basis of the

difference in mean-square error between the simulated eye movement and the measured values. The results are shown in more detail in Figure 6-6.
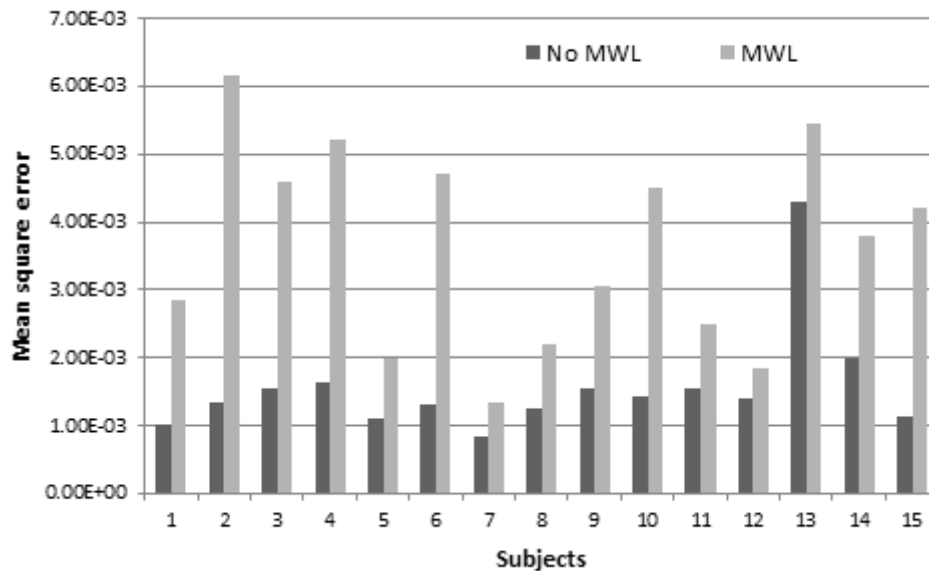
Figure 6-6. Average mean square error with offset for each subject

Our results showed a better performance than those previously obtained by Obinata and co-workers (Obinata et al. 2009) (Usui et al. 2007) (Obinata et al. 2008) (Obinata & Tokuda 2008). The difference between the case with an MWL and that in its absence was clearer than the previous case, in which the average mean-square error for no MWL was 1.56E–03 and that with an MWL was 3.48E–03 (more than two times). On the other hand, in previous researches, the participants focused one fixed point and the computer controlled the seat movement. In our study, the subject changed their gaze throughout the study, which is much closer to actual behavior when driving.

6.2. Evaluating driver distraction with stimulus environment

6.2.1. Experiment

Nine subjects were participated in the experiment. The experiments were approved by the Nagoya University's Institute of Innovation for Future Society Ethical Review Board. All subjects were provided with explanations regarding the

experimental procedure and gave their written informed consent. In the experiment, the participants drove to follow the designed course thrice with different level of distraction: without mental workload (MWL), with MWL 3s, and with WM 2s. The detail of the mental workload task is explained below.

To induce the mental workload, n-back task was applied. In this study, one number was verbally presented to the participial every 2 seconds (MWL 2s) or 3 seconds (MWL 3s). The subjects were asked to press the "Yes" or "No" button when the same or difference number reappeared compare with previous one.

The subject was asked to drive following the course (Figure 6-8) on the seat of a driving simulator with six degrees of freedom around 60km/h. To examine the natural eye movement, we was not have any instruction at all for the subjects.

The simulator was controlled by CarSim (Mechanical Simulation Co.) which can simulate the dynamic behavior of a vehicle (Figure 6-7). In these experiments, by using MATLAB Simulink (MathWorks) to control CarSim, the seat was moved with a fixed frequency in the vertical and horizontal plane (Figure 6-9).

Figure 6-7. Overview of the experimental setup
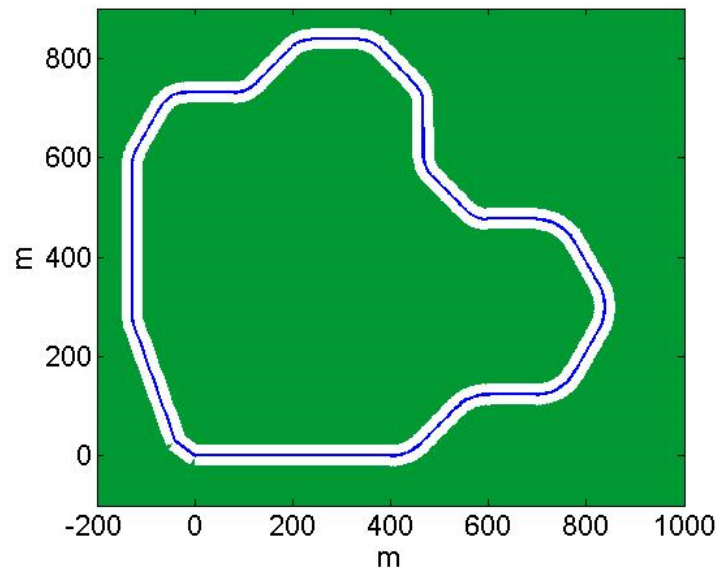
Figure 6-8. Plan of the course used in the experiment
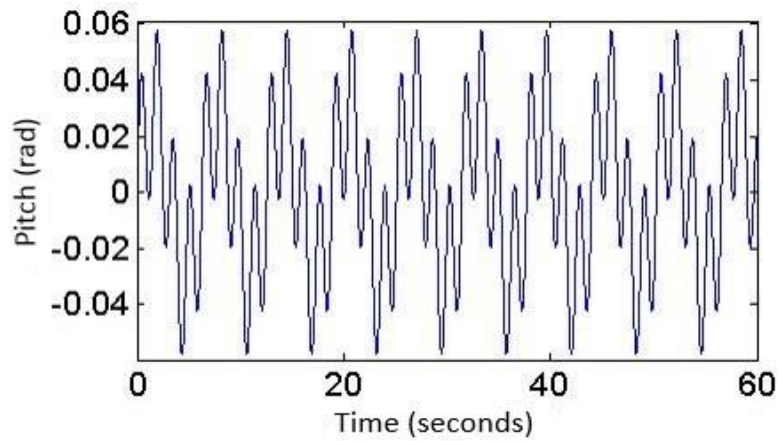
Figure 6-9. Input for seat movement

6.2.2. Results

Based on the difference between simulation and measurement of the eye movement (mean square error), the shorter interval the 1-back task is, the more the mean square error becomes (table 6-3).

Table 6-3. Mean square error of the eye movement of each subject

	No MWL	MWL 3s	MWL 2s	3s/No MWL	2s/No MWL
S1	2.90E-03	4.03E-03	4.20E-03	1.39	1.45
S2	3.87E-03	4.63E-03	4.74E-03	1.20	1.22
S3	2.70E-03	3.90E-03	6.10E-03	1.44	2.26
S4	6.10E-03	7.40E-03	9.40E-03	1.21	1.54
S5	2.53E-03	4.10E-03	4.40E-03	1.62	1.74
S6	3.40E-03	3.50E-03	5.60E-03	1.03	1.65
S7	2.50E-03	4.10E-03	4.60E-03	1.64	1.84
S8	5.44E-03	7.81E-03	1.06E-02	1.44	1.95
S9	2.60E-03	3.10E-03	3.50E-03	1.19	1.35

Following Table 6-3, the ratio of mean square error between driving with 1-back task 3s (3 second interval) and driving without mental workload increase from 1.03 to 1.64. Moreover, the driver drove with 1-back task 2s (2 second interval, more difficult) showed worse performance compare with 1-back task 3s. The ratio between 2s and without mental workload was larger, its increases from 1.22 to 2.26 depend on individual.

To examine more detail, the figures of eye movement in two cases (without and with mental workload) shows in Figure 6-10 and Figure 6-11.
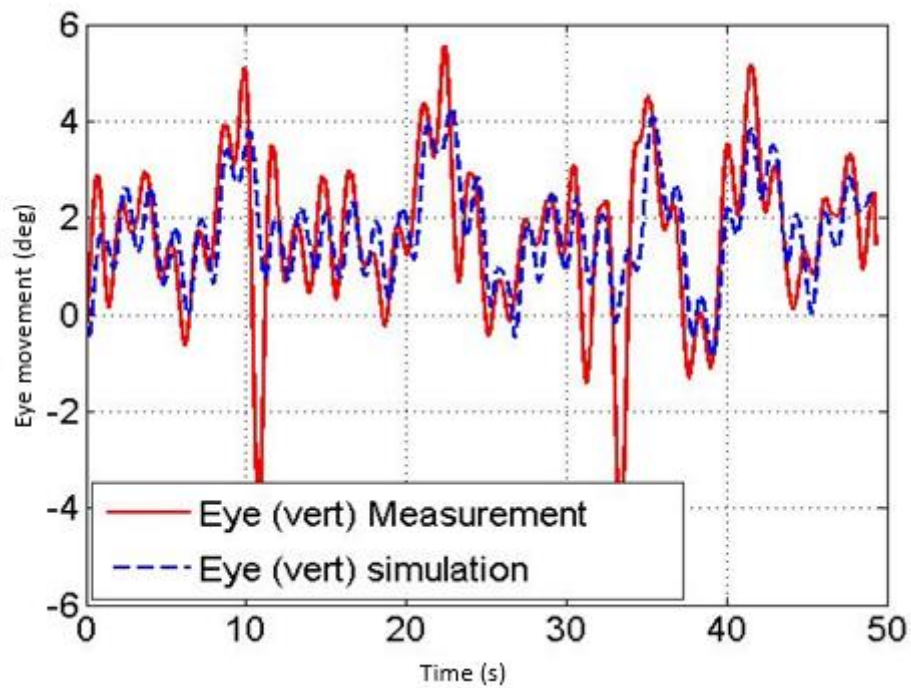
Figure 6-10. Driving without mental workload (Subject 3)
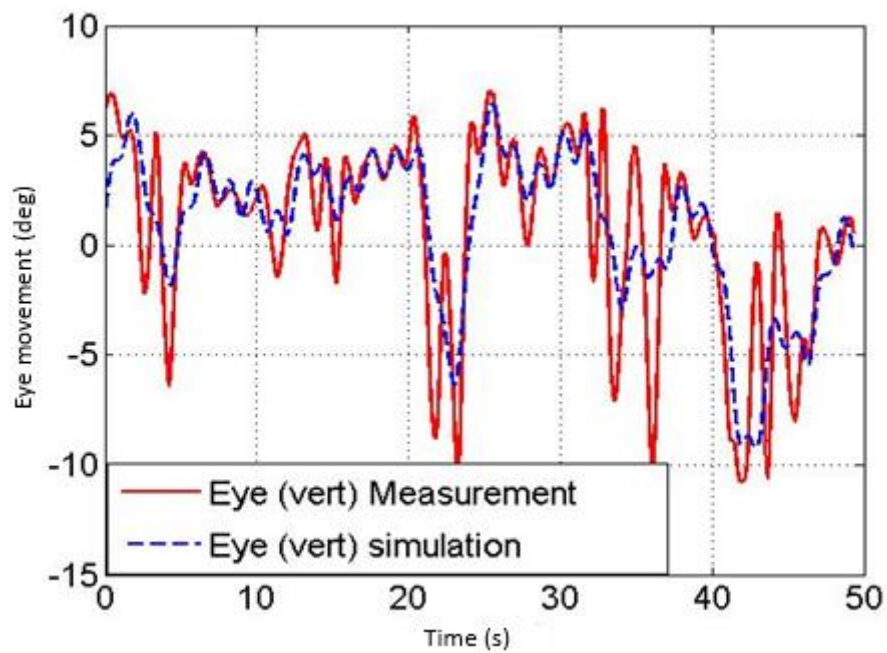
Figure 6-11. Driving with mental workload 2 – seconds (subject 3)

Based on Figure 6-10 and Figure 6-11, the result showed that while driving with mental workload, the time and frequency became mismatched.

Furthermore, a boxplot of the mean square error is shown in Figure 6-12. Based on the distribution of the mean square error, in case of no MWL, the mean of mean square error was lowest with 2.9e-03 (MWL 3s: 3.1e-03; MWL 2s: 4.7e-03). It means that the gap between eye observed and simulated can be estimated as the level of driver distraction.
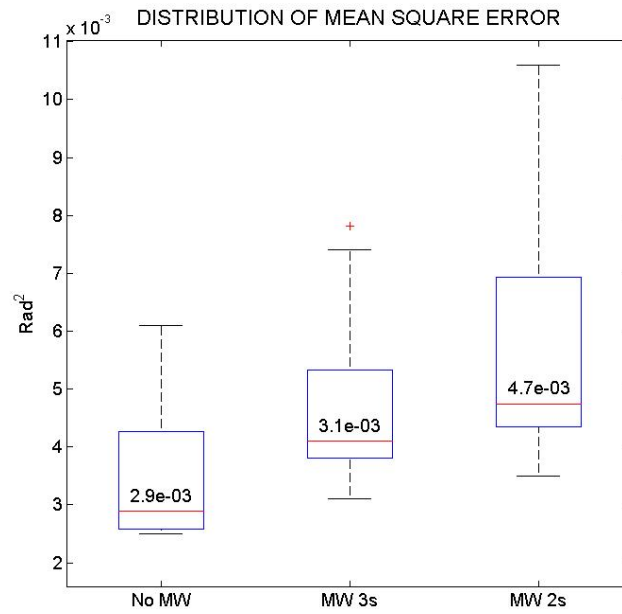
Figure 6-12. Distribution of mean square error
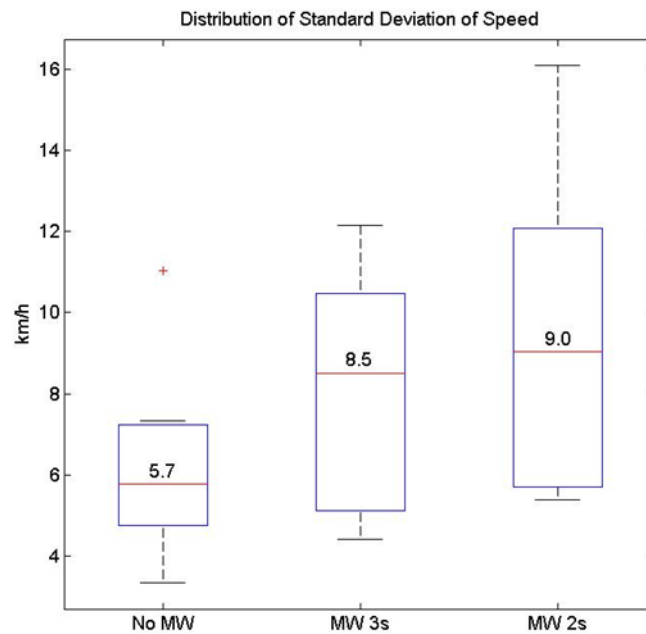
Figure 6-13. Distribution of the speed standard deviation

The speed standard deviation is one of importance information that had the correlation with traffic accident. In this study, the driver speed was recorded and used as driving performance. The distribution of standard deviation of speed was shown in Figure 6-13. The results indicated that: the harder of MWL was presented the bigger standard deviation of speed was shown. It means that the driving performance became worse under distraction.

Furthermore, the ANOVA analysis was made with main purpose to see the effect of MWL on driver distraction. The results will be shown in table 6-4.

Table 6-4. ANOVA results

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
MWL	2	2.01E-01	1.05E-01	4.71	1.88E-02*
Residuals	24	5.36E-01	2.22E-02		
Signif. codes: '***' : p<0.001 '*': p<0.05					

The results showed in table 6-4 indicated that:

- Mental workload has a significant effect on the MSE between eye simulation and measurement. It confirmed that the model can be indicated the driver distraction while driving.

6.3. Effect of aging and mental workload on eye movement

6.3.1. Introduction

· **Aging problem**

Currently, the aging of population occurs in most countries in the world, especially in developed countries. For example, according to the statistics in Japan, the percentage of people with age 65 and over increases year by year. In 2014, the percentage of people with age over 65 years old is 26.0%. It increases to 39.9% in 2060 (Anon 2015a).

As suggested by previous researches, aging cause a complex issue that include transportation especially driver distraction (Arai & Arai 2015) (Restrepo & Rozental 1994) (Stinchcombe & Gagnon 2013) (Son et al. 2015) (Donmez & Liu 2015) (Curry et al. 2015). For example, Thompson, et al. found out that older drivers made more driving safety error than middle-aged drivers while completing an audio serial addition task (Thompson et al. 2012). In order to support old drivers, we need to develop a method to evaluate driver distraction based on behavior.

· **Effect of aging on driver distraction**

The influent of aging and distraction while driving was investigated by several researchers (Mouloua et al. 2004) (Cantin et al. 2009) (Fofanova & Vollrath 2011) (Son et al. 2015) (Anon 2015b) (Stinchcombe & Gagnon 2013) (Aksan et al. 2013) (Anh Son et al. 2016). Almost study confirmed that older people doing secondary task while driving shown worse performance compare with younger driver.

In this chapter, by using the driver recorded and the comparison between simulation and measurement of eye movement, the effect of aging and mental workload on driver performance that include the SSD and distraction level was investigated.

6.3.2. Method

· **Experiment setup**

In the experiment, subjects were asked to drive by following a course on the seat of a driving simulator with six degrees of freedom. The driving simulator had a cylindrical 360° screen of 6 m in diameter. The simulator was controlled by CarSim (Mechanical Simulation Co.) which can simulate the dynamic behavior of a vehicle (Figure 6-14). By controlling CarSim with MATLAB Simulink (MathWorks), the seat was moved at a prefixed frequency on the vertical and horizontal planes.

In this study, the participant followed the course with visual stimulus by mean of driving simulator. Eye movement was captured by using Smart Eye pro (Smart Eye AB) with four cameras on the dashboard. To collect information on movements of the head, we used a Fastrak electromagnetic tracker (Polhemus Inc.).

Figure 6-14. The experimental setup of the driving simulator

An n-back task was used to create driver distraction. In the present n-back task, a series of one-digit numbers was verbally presented at an interval of 2 seconds. The subject was asked to judge whether or not each number was equal to preceding one and respond by pressing buttons on the steering wheel.

In order to simulate vibration of the vehicle, the seat was moved by the control of CarSim with MATLAB Simulink. The seat vibration consists of two components: vertical and horizontal. Figure 6-15 shows the profile of input for the seat vibration.
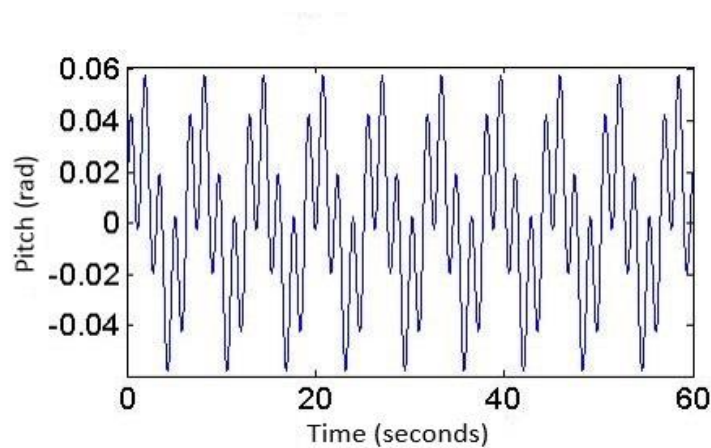
Figure 6-15. Input for seat movement

· **Eye Simulation model**

The same with previous, the development model which consisted both VOR and OKR will be used to simulate eye movement.

In this experiment, the total 12 participants were divided into two group: younger (less than 60 years old) and older (60-year-old and above). The experiments were approved by the Nagoya University's Institute of Innovation for Future Society Ethical Review Board. All subjects were provided with explanations regarding the experimental procedure and gave their written informed consent.

6.3.3. Results and discussion

·   **VOR and OKR interaction**

To confirm a new model combined VOR and OKR models, we compared the eye movement of two cases: only VOR model and VOR/OKR model without mental workload. By comparing the observed eye movement and the simulation results from the models, the VOR/OKR model showed lesser mean square error than the VOR model only. For example, the mean square error of the observed eye movement and calculated one from the model reduced from 1.1E-03 to 4.3E-04 in Subject 18. We confirmed similar results in other subjects. Moreover, Figure 6-16 shows that by combining OKR model, the simulation provides better matching.
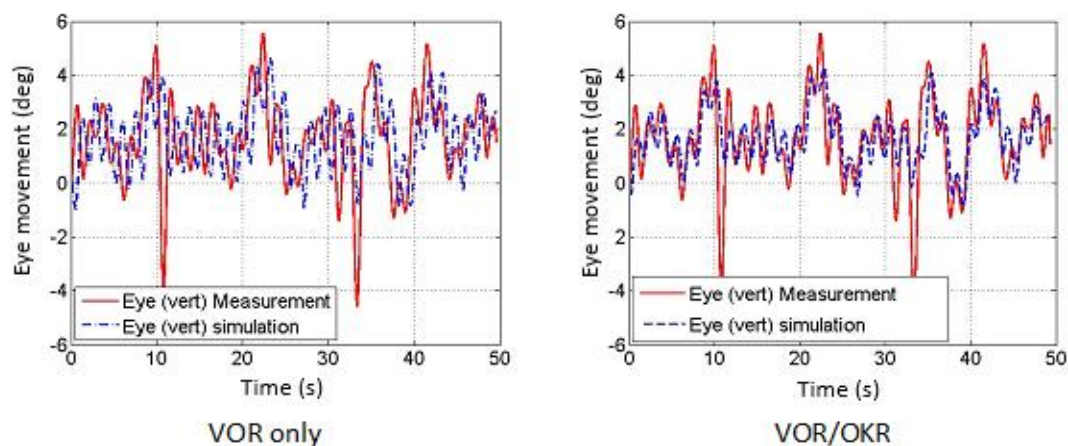
Figure 6-16. Eye movement

As a result, the model consists of both VOR and OKR shows better performance compared with VOR model only.

·   **Effect of driver distraction on eye movement**

In this study, the effect of n-back task on driver distraction was evaluated by using the mean-square error between the measured and simulated eye movement in both vertical and horizontal direction.

All subjects participated in this experiment with two trials: drive without mental workload and drive with mental workload. The eye movement was simulated based on head movement using VOR/OKR model.

- *Younger group*

Without mental workload   With mental workload
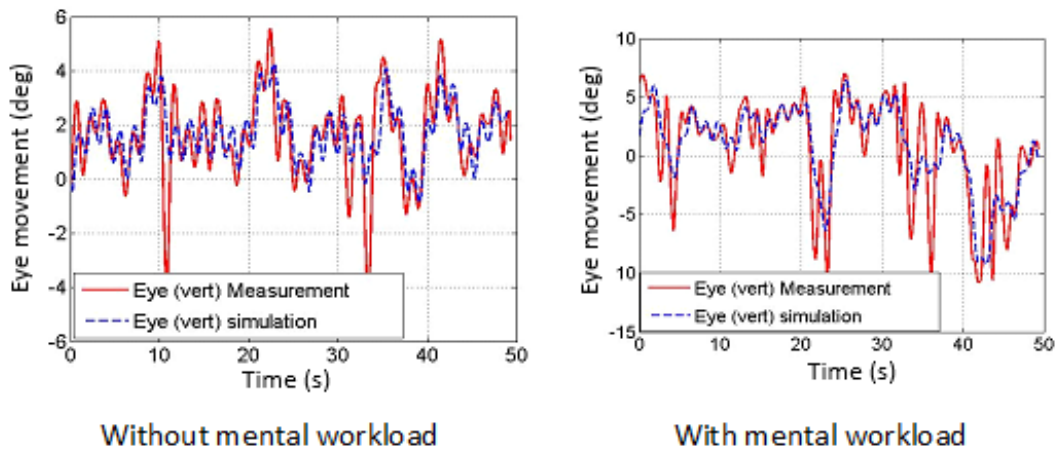
Figure 6-17. Driving without/with mental workload (example of Subject 18)

Figure 6-17 shows an example of the eye movement in vertical direction without and with mental workload for total 50 seconds. In this case, the mean square error for vertical direction without mental workload was 4.3E-04 and it increased to 1.9E-03 with mental workload.

As shown in Figure 6-17, the time and frequency response became mismatched with mental workload. Consequently, the mean square error increased from the case without mental workload. We found similar results in other subjects in younger group (Table 6-5).

Table 6-5. Mean square error of each younger subject

Subject	Without mental workload			With mental workload			Ratio of With/Without
	Horizon	*Vertical*	*Total*	*Horizon*	*Vertical*	*Total*	
S13	4.1E-03	2.0E-03	6.1E-03	4.7E-03	4.7E-03	9.4E-03	1.54
S14	2.0E-03	5.3E-04	2.5E-03	2.7E-03	1.7E-03	4.4E-03	1.74
S17	3.2E-03	1.0E-03	4.2E-03	3.9E-03	1.3E-03	5.1E-03	1.23
S18	1.7E-03	4.3E-04	2.1E-03	2.8E-03	1.9E-03	4.7E-03	2.20
S21	1.0E-03	5.0E-04	1.5E-03	1.4E-03	8.3E-04	2.2E-03	1.46
S22	2.4E-03	7.8E-04	3.2E-03	2.6E-03	1.8E-03	4.4E-03	1.38

- *Older group*

The results of older group show the same trend with young people. The mean square error was increased in the condition with mental workload. Figure 6-18 shows an example of subject.
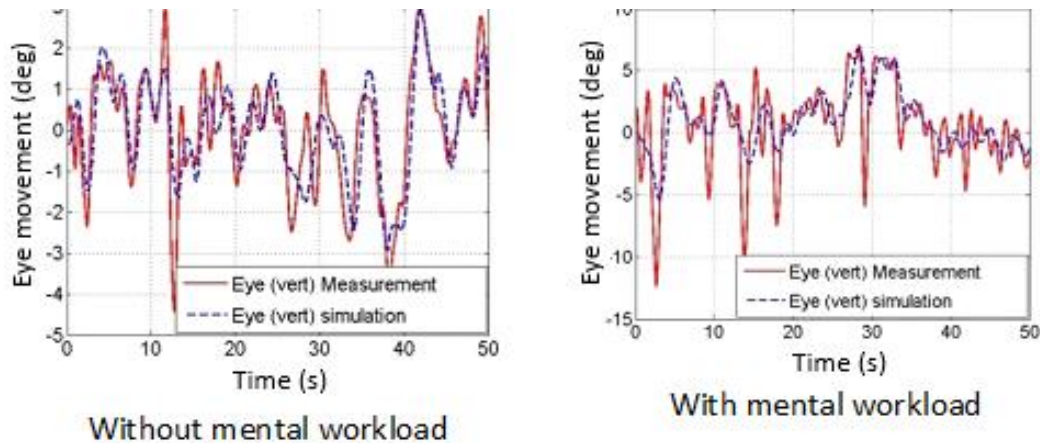
Figure 6-18. Driving without/with mental workload (example of Subject 9)

In the case of driving without mental workload, the eye movement of subject 9 matched well in both time and frequency response. Inversely, when the subject 9 drove with mental workload, the simulation became mismatched and it increased the mean square error.

Table 6-6. Mean square error of each older subject

Subject	Without mental workload			With mental workload			With/
	Horizon	Vertical	Total	Horizon	Vertical	Total	Without
S1	2.5E-03	4.0E-04	2.9E-03	3.0E-03	1.2E-03	4.2E-03	1.45
S2	3.5E-03	3.8E-04	3.9E-03	4.0E-03	7.4E-04	4.7E-03	1.22
S4	1.5E-03	1.2E-03	2.7E-03	4.4E-03	1.7E-03	6.1E-03	2.26
S9	1.7E-03	2.3E-04	1.9E-03	2.8E-03	1.4E-03	4.2E-03	2.17
S10	2.3E-03	2.0E-03	4.3E-03	2.4E-03	3.7E-03	6.1E-03	1.42
S12	5.4E-03	9.2E-04	6.3E-03	1.1E-02	2.4E-03	1.4E-02	2.17

In the same way with younger group, the mean square errors were higher in the condition with mental workload. The rates of increase in the error from 1.22 times to 2.17 times. We once again confirmed that the older drivers are more distracted by the secondary task.

- *Cross effect*

Figure 6-19 compares the increase of the mean square error between older and younger groups. The mean square error of older group increased more sharply than that of younger group (for older group, the average of mean square error from 3.7E-03 without mental workload to 6.5E-03 with mental workload. On the other hand, younger group got small larger with average from 3.3E-03 to 5.0E-03). This means that older people were more distracted when driving with the secondary task.
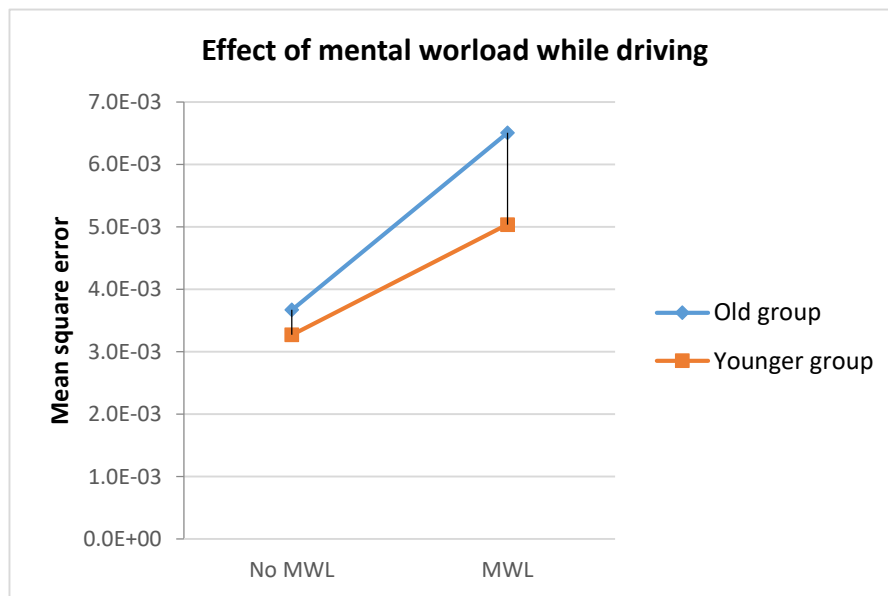
Figure 6-19. Effect of metal workload while driving

CHAPTER 7: EVALUATION OF DRIVER DISTRACTION IN ACTUAL VEHICLE

7.1. Evaluating driver distraction in the passenger's seat

7.1.1. Experimental setup

In this experiment, in total the data from 13 subjects were collected. The experiments were approved by the Nagoya University's Institute of Innovation for Future Society Ethical Review Board. All subjects were provided with explanations regarding the experimental procedure and gave their written informed consent. For the safety reason, a participant was asked to sit on the passenger seat. The driver drove the car in a private closed course 4 times: two times at 15 km/h and two times at 30 km/h (Table 7-1).

Table 7-1. Experiment condition

		Mental Workload	
		Without	With
Vehicle's	15km/h	Condition 1	Condition 2
Velocity	30km/h	Condition 3	Condition 4

At one condition of the speed, the participant was asked to relax for the first time and to answer an n-back task in the second times. The participants were worn the EyeSeeCam (EyeSeeTec GmbH) to capture the eye and head movement (Figure 7-1).

Figure 7-1. Experiment setup

The EyeSeeCam is the eye tracker by cameras using infrared reflecting hot mirrors. In this experiment, the raw head and eye measurement was captured by EyeSeeCam and it was filtered for analysis.

EyeSeeCam technical Specifications

Sample rate: 220Hz

Head tracking sensor: Inertial Measurement Unit (IMU) gyroscope with 6 degrees of freedom

Gain: 40, 60 and 80 ms

Operating voltage: 5V

Figure 7-2. EyeSeeCam

In this research, we used a round trip straight route in a private road. During the experiment, there were sometimes other traffic such as pedestrian, bicycle, motorbike, and car.

·   N-back task

To impose a mental workload during driving, the n-back task of digit recall was used (Figure 7-2). In our n-back task, one number was verbally presented to the subject every one second. The subjects were asked to press the "Yes" when the

number that appear was the same as the previous ones and the "No" button when it was different.
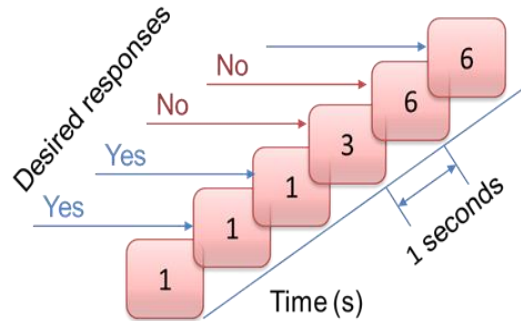
Figure 7-3. N-back task

7.1.2. Methodology

With the same processing in Chapter 6, in this experiment, the first ten seconds of the experiment in condition 1 is used for running parameter identification for each individual. And then, the set of the parameter is applied for simulating eye movement in all conditions by using VOR+OKR model.

7.1.3. Results

·   Effect of speed on eye movement simulation

The vehicle's velocity has a strong impact on vehicle's vibration. The vibration of the vehicle is effected by a lot of elements such as road condition, shock absorber, vehicle weight, and so on. In this research, the speed had an effect on the vibration
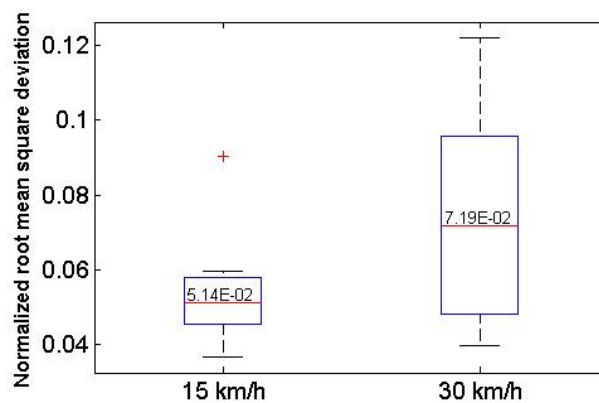
that would be the main cause of head movement. Therefore, due to the difference of speed, the measured head movement and the eye movement was different.

Figure 7-4. Normalized root mean square deviation (at 15km/h and 30 km/h)

As in the Figure 7-4 shown, at higher speed, the NRMSD was increased. Inversely, when the driver drove slower, the NRMSD was smaller (at 15km/h, NRMSD equal 5.14E-02, at 30km/h, NRMSD equal 7.19E-02).

The increase of NRMSD may be caused by the difference of vibration while driving. As shown in figure 7-6, the eye movement at 30km/h was much different compared with 15km/h (figure 7-5).
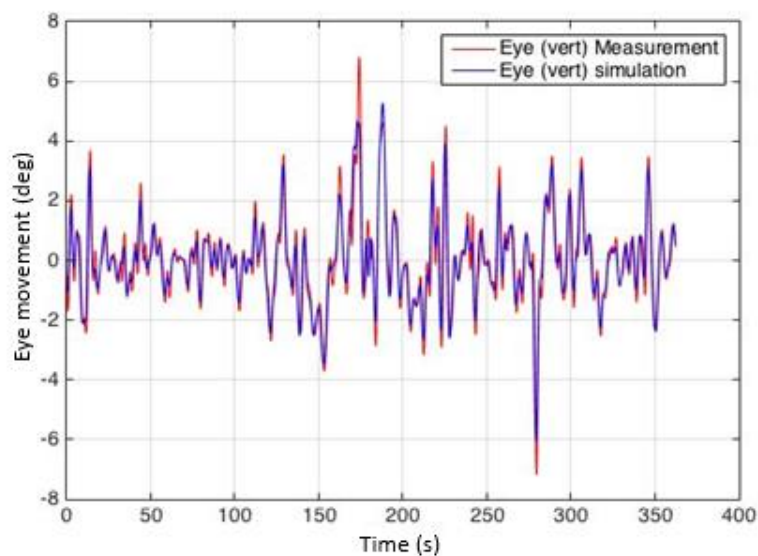
Figure 7-5. Eye simulation for subject 13 (W/O mental workload at 15km/h)
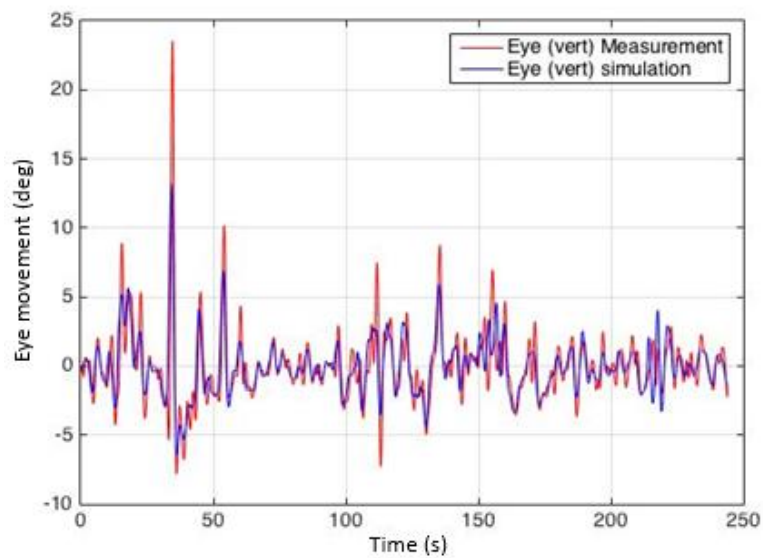
Figure 7-6. Eye simulation for subject 13 (W/O mental workload at 30km/h)

·   Effect of mental workload on eye movement

Based on the data analysis, the results shown the NRMSD between the simulated and observed eye movement became larger in the presence of mental workload. The median of NRMSD in case of without MWL is 5.74E-02, and it increases to 7.33E-02 in case of with MWL (Figure 7-7). Table 7-2 shows more details of NRMSD of each subject in the experiment.
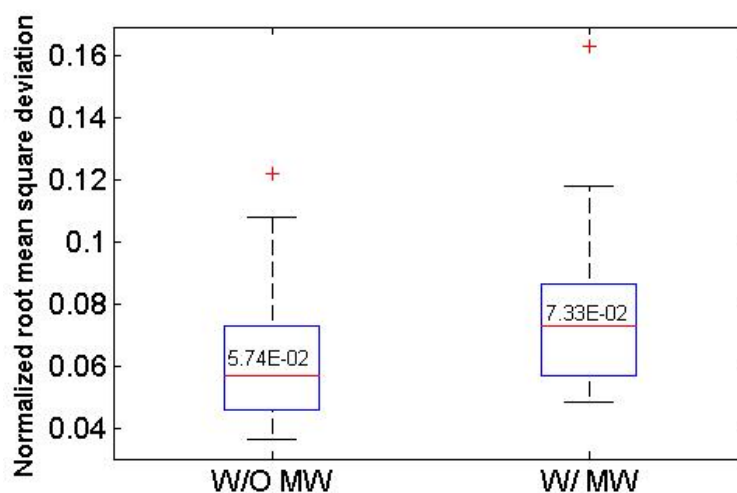
Figure 7-7. Normalized root mean square deviation (W/ and W/O MWL)

Among 13 subjects, all of them showed the same trend with the increasing of NRMSD while going with MWL. This confirmed that this method can detect driver cognitive distraction by using the difference between simulation and measurement of eye movement in actual condition.

Table 7-2. NRMSD of each subjects

	15km/h			30km/h		
	W/O MWL	*W/ MWL*	*Ratio*	*W/O MWL*	*W/ MWL*	*Ratio*
S1	4.43E-02	4.94E-02	1.12	4.52E-02	4.87E-02	1.08
S2	5.96E-02	7.29E-02	1.22	7.31E-02	7.72E-02	1.06
S3	4.72E-02	6.63E-02	1.40	4.91E-02	7.97E-02	1.62
S4	9.02E-02	1.01E-01	1.12	1.08E-01	1.11E-01	1.03
S5	4.79E-02	5.12E-02	1.07	9.66E-02	1.05E-01	1.09
S6	5.14E-02	5.17E-02	1.01	6.08E-02	6.36E-02	1.05
S7	5.29E-02	7.37E-02	1.39	7.66E-02	8.01E-02	1.05
S8	5.76E-02	6.28E-02	1.09	9.55E-02	1.18E-01	1.23
S9	5.72E-02	6.88E-02	1.20	1.22E-01	1.63E-01	1.33
S10	3.68E-02	5.70E-02	1.55	4.51E-02	7.68E-02	1.70
S11	3.91E-02	5.54E-02	1.42	3.99E-02	5.02E-02	1.26
S12	4.60E-02	6.11E-02	1.33	7.19E-02	8.69E-02	1.21
S13	5.96E-02	8.15E-02	1.37	6.96E-02	9.48E-02	1.36

To deeply looked at the difference in case of with and without mental workload, the eye simulation and eye measurement in both cases were shown in Figure 7-8 and Figure 7-9.
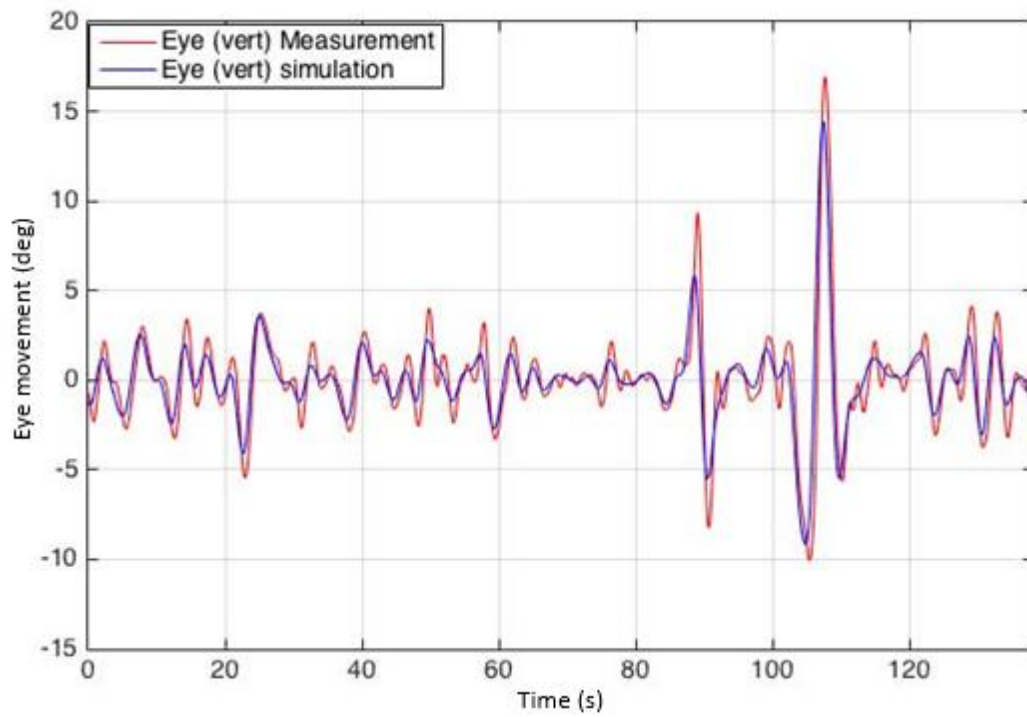
Figure 7-8. Subject 3 – Without MWL at 15km/h
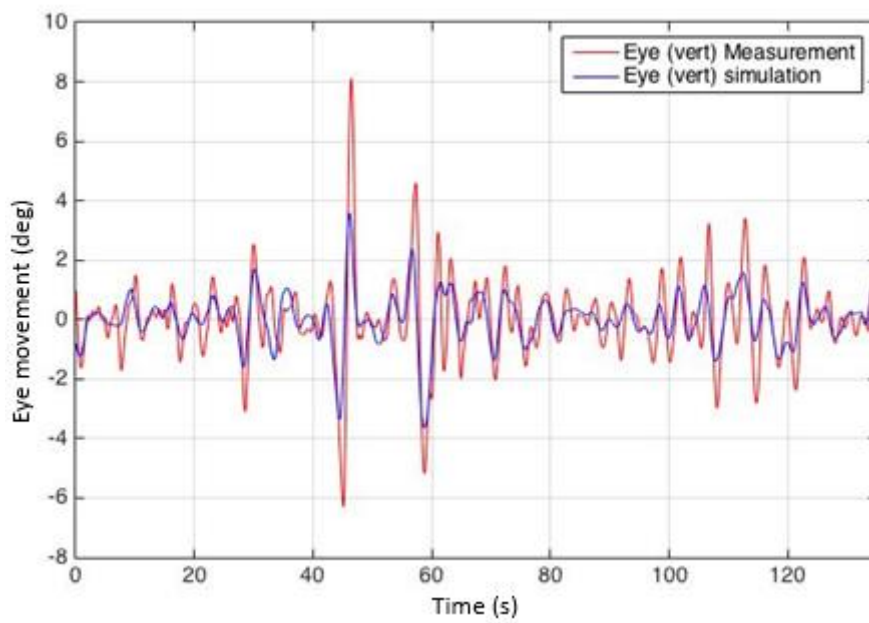
Figure 7-9. Subject 3 – With MWL at 15km/h

The results once again confirmed that, in the present of n-back task, the eye movement simulation became miss matching in both time response and magnitude response.

·　　　ANOVA analysis

Furthermore, an ANOVA analysis was applied with the main purpose to see the effect of speed and mental workload on driver distraction. The result will be shown in table 7-3.

Table 7-3. ANOVA results

	Df	*Sum Sq*	*Mean Sq*	*F value*	*Pr(>F)*
Speed	1	6.16E-03	6.16E-03	12.52	8.91E-04***
MWL	1	2.56E-03	2.56E-03	5.2	2.70E-02*
SP:MWL	1	2.90E-05	2.90E-05	0.06	0.81
Residuals	48	2.41E-02	5.01E-04		
Signif. codes: '***' : p<0.001　　'*': p<0.05					

Like the previous results, ANOVA for the model once again shown a significant effect (F=5.2, p<0.05), it confirmed that this method can detect mental workload while driving by comparing the eye simulated and measured.
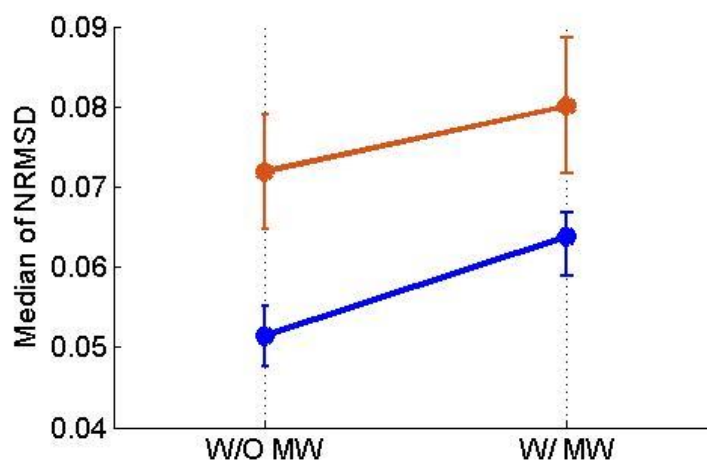
Figure 7-10. NRMSE

On the other hand, in case of 15km/h, the NRMSD increased from 5.14E-02 to 6.28E-02. In the same trend, the NRMSD was growth up from 7.19E-02 to 8.01E-02 in case of 30km/h. In addition, in ANOVA results, the interaction between speed and mental workload was not significant. It means that the relationship between mental workload and driver distraction do not depend on speed. On the other hand, the ANOVA results also indicated that the velocity of vehicle has strongly effect on the difference of eye measurement and simulation. It may cause by the vehicle's vibration in difference velocity, and it leaded to the difference input for eye movement simulation that made the NRMSD became difference.

7.2. Evaluating driver distraction in driver's seat

In the same experiment with previous, here, we applied to evaluate for the driver who control the vehicle in an actual situation with natural vibration. With a central goal to confirm the method can apply with driver, total 9 subjects were joined this experiment. The experiments were approved by the Nagoya University's Institute of Innovation for Future Society Ethical Review Board. All subjects were provided with explanations regarding the experimental procedure and gave their written informed consent.

Figure 7-11. Experiment setup

To imposed n-back task, the same with previous, one number will be presented every two seconds. The driver was asked to push two buttons that installed in steering wheel to answer.

The driver drove the car in a private closed course 4 times: two times at 15 km/h and two times at 30 km/h (Table 7-4).

Table 7-4. Experiment condition

		Mental Workload	
		Without	With
Vehicle's	15km/h	Condition 1	Condition 2
Velocity	30km/h	Condition 3	Condition 4

· **Results**

Table 7-5 present the results of normalization root mean square error for each subject.

Table 7-5. NRMSE of each subject

	15km/h			30km/h			Base line (30/15)
	W/O MWL	W/ MWL	Ratio (1)	W/O MWL	W/ MWL	Ratio (2)	Ratio (3)
S1	0.063	0.147	2.317	0.068	0.101	1.490	1.07
S2	0.080	0.141	1.765	0.105	0.197	1.873	1.32
S3	0.047	0.121	2.562	0.072	0.158	2.187	1.53
S4	0.119	0.160	1.346	0.133	0.146	1.092	1.12
S5	0.102	0.207	2.022	0.134	0.225	1.680	1.31
S6	0.051	0.191	3.706	0.078	0.222	2.850	1.52
S7	0.123	0.139	1.133	0.140	0.164	1.173	1.14
S8	0.130	0.172	1.325	0.137	0.147	1.075	1.05
S9	0.108	0.161	1.494	0.124	0.131	1.061	1.15

Ratio (1): 15km with MWL/15km without MWL

Ratio (2): 30km with MWL/ 30km without MWL

Ratio (3): 30km without MWL/ 15km without MWL

Same with the previous one, among 9 subjects, all of them showed the same trend with the increasing of NRMSD while going with MWL. This confirmed that this method can detect driver cognitive distraction by using the difference between simulation and measurement of eye movement in actual condition.

Furthermore, the results noted that the increases of speed may lead to the increase of NRMSE. It means the speed somehow has the relationship with the mental workload. Or maybe, to prevent the accident, the driver becomes more stressful and the brain has to process more information of the environment, it made the eye become miss matching sometime.
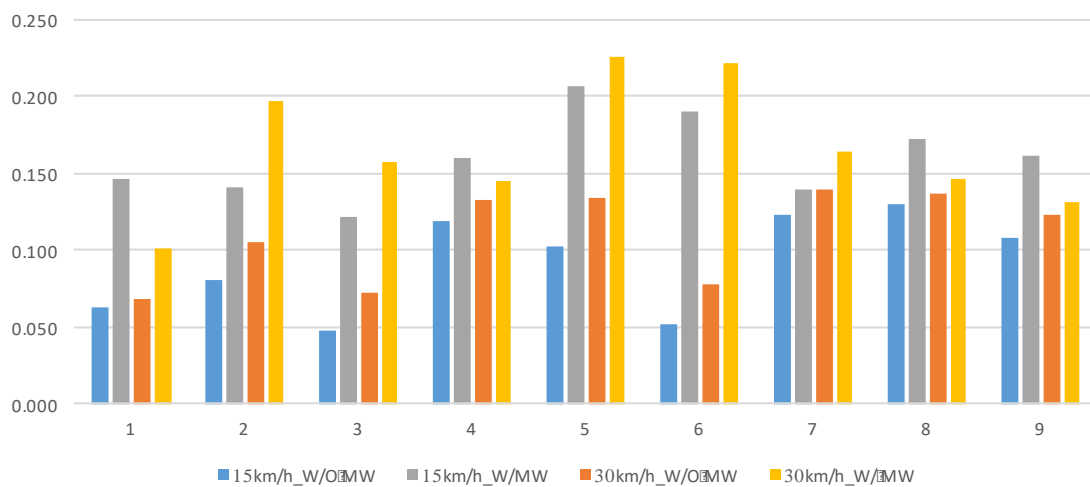
Figure 7-12. Distribution of NRMSE

· ANOVA analysis

Moreover, an ANOVA analysis was applied with the main purpose to see the effect of speed and mental workload on driver distraction. The result will be shown in table 7-6.

Table 7-6. ANOVA results

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Speed	1	1.34E-03	1.34E-03	1.23E+00	2.76E-01
MWL	1	3.46E-02	3.46E-02	3.16E+01	3.25E-06***
SP:MWL	1	3.70E-04	3.70E-04	3.41E-01	5.63E-01

Residuals	32	3.50E-02	1.09E-03		
Signif. codes: '***' : p<0.001					

One more time, the ANOVA results again indicated a significant effect ($F=3.16$, $p<0.001$), it confirmed that this method can detect mental workload while driving by comparing the eye simulated and measured.

Take a look more detail for eye movement with different speed in case of without MW in figure 7-13 and 7-14.
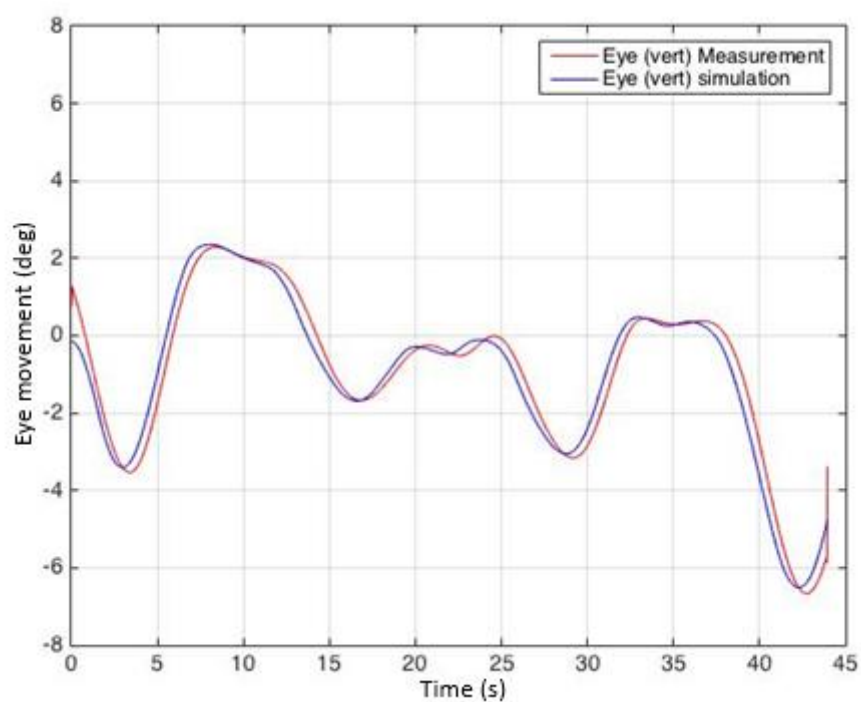
Figure 7-13. Eye movement at 15km/h – Without MWL (S3)
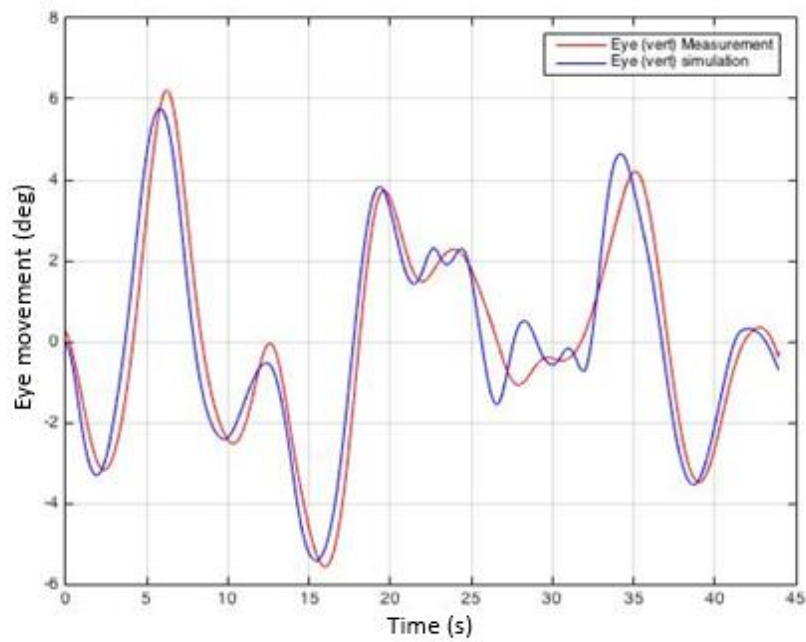
Figure 7-14. Eye movement at 30km/h – Without MWL (S3)

With the similar about course, driver, condition, the eye movement at 30km/h had a bigger frequency and magnitude compared with 15km/h. It happened because of the different of vibration in different speed condition.
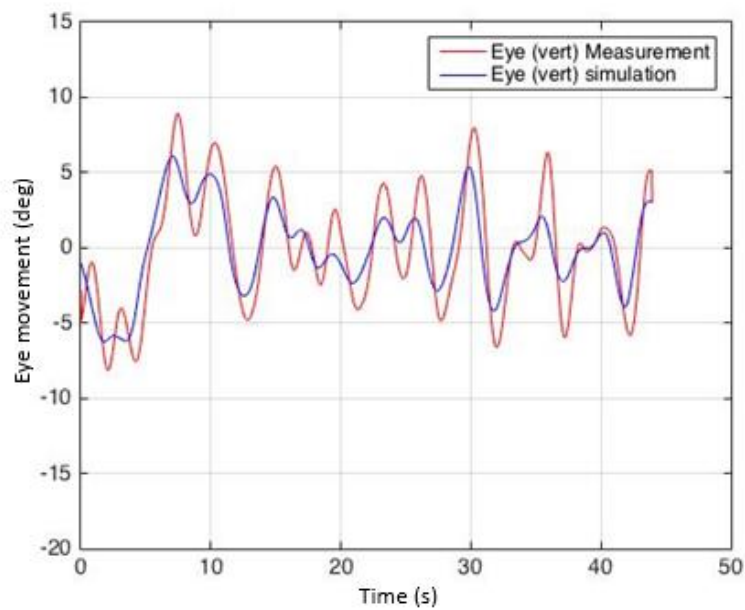
Figure 7-15. Eye movement at 15km/h – with MWL (S3)
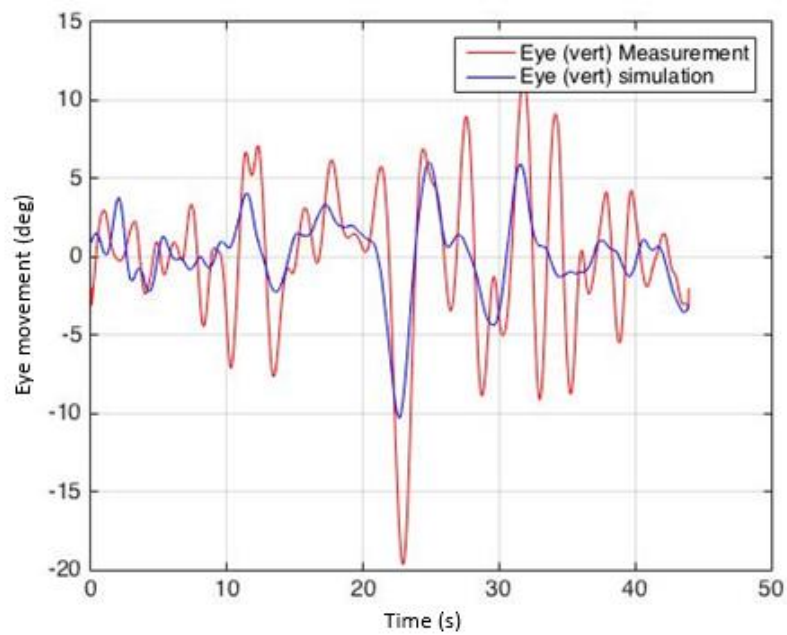
Figure 7-16. Eye movement at 30km/h – with MWL (S3)

In cases with MWL, the eye became miss matching in both frequency and magnitude. The eye movement became unpredictable.

Taken all results together, the data demonstrate that the drivers' mental workload can be evaluated by using involuntary eye movement by comparing the simulation and measurement. In addition, the results also indicated that the model consisted VOR with OKR works well in natural situations.

CHAPTER 8:   CONCLUSION AND FUTURE WORK

8.1.   Conclusions

8.1.1.   Parameter identification

With the main purpose to improve the accuracy of the VOR model while simulates eye movement. The parameter identification toolbox was developed by changing the initial input. The results indicated that:

- Genetic algorithm applied to identify parameter of the VOR model shows better performance than that of Merfeld and Zupan parameters and the previous hybrid GA.
- The parameters of individuals depend on the characteristics of each person. An individual has an identical set of parameters. To find the relationship between parameter and individual information, we need further experiments.
- This experiment, included some errors that changed the parameters due to the manual seat adjustment. We need mechanically controlled apparatus in order to reduce errors for more precise parameter identification.
- The successful creation of a toolbox can identify parameters for the VOR model with the more exact ability and reliability. This toolbox supports various kinds of eye and head tracking devices.

By improving the exact ability for identifying parameters of VOR model, the VOR model can be applied for simulating eye movement with higher accuracy even in gaze transition. It may be possible to apply VOR model for evaluating driver distraction as well as to change vehicle dynamic based on simulation brake motion.

8.1.2.   VOR + OKR model

During the simulation eye vertical movement for drivers in the natural situation, the combination of the VOR and OKR was investigated. The results of the combination confirmed that:

- The model that consists of both VOR and OKR shows better performance than VOR model not only in the condition without visual stimulus but also in real situations.
- Recently findings on simulation eye movement has pointed out that the VOR+OKR can be simulated involuntary eye movement in an actual vehicle with the surrounding environment.

8.1.3. Evaluation drivers' mental workload

In sum, our research found that the model that consists of both VOR and OKR can estimate the driver distraction while driving by comparing the eye simulation and eye measurement not only in driving simulator but also in actual vehicles.

The results in chapter 7 also confirmed that the older people show worse performance than younger, especially under distracted driving. It means that they need more support from technology while driving to reduce the mental workload.

8.2. Future Works

In this study, we also noticed that there are differences in personal reflex eye movements. It means that we have to identify model parameters for each individual. To achieve online detection of driver distraction, the parameter-identification time should be reduced by identifying the trend in each parameter of our model with larger samples and then reducing the number of parameters by fixing some parameters that show little variation between subjects. Moreover, we hope that as computer science progresses, the parameter-identification time might be reduced from the current ten minutes to one minute or less.

Due to the limitation of speed condition, the effect of speed on the eye simulation model was not so clear. In the near future, we will try to collect more data by changing the speed condition and road condition to clearly see the effect of them on the model.

In the future, to confirm the robustness of the model, tests will need to be conducted in a complex visual environment in virtual and real situations. Moreover, because of the limited sample size, the effects of driver characteristics were not analyzed in this study. Future studies should pay more attention to individual differences in the model parameters as well as integrating the reflex-eye-movement

method into other methods for assessing driver/vehicle behavior to obtain a more precise evaluation of driver distraction.

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