UNIVERZITA
PARDUBICE
DOPRAVNÍ
FAKULTA
JANA PERNERA

The University of Pardubice

Faculty of Transport Engineering

Traffic evaluation using camera recording

Master's Thesis

2025 Mohammad Abu Asad

PARDUBICE 2025

Univerzita Pardubice
Dopravní fakulta Jana Pernera
Akademický rok: 2023/2024

ZADÁNÍ DIPLOMOVÉ PRÁCE

(projektu, uměleckého díla, uměleckého výkonu)

Jméno a příjmení:	**Bc. Mohammad Abu Asad**
Osobní číslo:	**D22451**
Studijní program:	**N0788A040001 Dopravní technika**
Specializace:	**Provoz a údržba vozidel**
Téma práce:	**Traffic evaluation using camera recording**
Zadávající katedra:	**Katedra dopravních prostředků a diagnostiky**

Zásady pro vypracování

Dopravní nehoda je situace, kdy dojde k odchylce od běžného standardu míjení provozů. V analýze dopravních nehod běžně řešíme právě tyto odchylky, nikoliv již běžný bezkolizní provoz. Pro posouzení odchylky konkrétního nehodového děje je třeba znát běžný standard míjení provozů. Práce je cílena na návrh a provedení metodiky vyhodnocování kamerových záznamů z míst křížení provozů s cílem nastavit zákonitosti pro běžné míjení provozů.
Student by ve své práci měl postihnout následující body:

1. Základní informace o obrazu a videozáznamu.
2. Vyhodnocování pohybu z videozáznamu.
3. Realizace porovnávacího měření – kamerový záznam vs. konvenční měřící technika.
4. Metodika vyhodnocování kamerových záznamů z místa křížení komunikací.
5. Sběr a analýza dat z reálné křižovatky.
6. Vyhodnocení analyzovaných dat z hlediska míjení provozů automobilů.
7. Závěr – shrnutí zjištěných poznatků a možnost jejich případného zobecnění.

Rozsah pracovní zprávy: **50 stran**
Rozsah grafických prací: **podle pokynů vedoucího práce**
Forma zpracování diplomové práce: **tištěná/elektronická**
Jazyk zpracování: **Angličtina**

Seznam doporučené literatury:

[1] RÁBEK, V.: *Technika moderních vozidel ve vztahu k objasňování dopravních nehod: (sborník českých a slovenských odborných prací).* Olomouc: Properus, 2020. ISBN 978-80-904944-3-5.
[2] HABART, L.: *Využití moderních kamerových systémů při analýze silničních nehod.* Diplomová práce, Vysoké učení technické v Brně, 2013, dostupné z: www.vut.cz/www_base/zav_prace_soubor_verejne.php?file_id=67676

Vedoucí diplomové práce: **Ing. Jan Pokorný, Ph.D.**
Katedra dopravních prostředků a diagnostiky

Datum zadání diplomové práce: **9. února 2024**
Termín odevzdání diplomové práce: **10. května 2024**

L.S.

doc. Ing. Libor Švadlenka, Ph.D.
děkan

Ing. Jakub Vágner, Ph.D.
vedoucí katedry

V Pardubicích dne 9. února 2024

I DECLARE:

The thesis entitled Traffic evaluation using camera recording is my own work. All literary sources and information that I used in the thesis are referenced in the bibliography. I have been acquainted with the fact that my work is subject to the rights and obligations arising from Act No. 121/2000 Sb., On Copyright, on Rights Related to Copyright and on Amendments to Certain Acts (Copyright Act), as amended, especially with the fact that the University of Pardubice has the right to conclude a license agreement for the use of this thesis as a school work under Section 60, Subsection 1 of the Copyright Act, and that if this thesis is used by me or a license to use it is granted to another entity, the University of Pardubice is entitled to request a reasonable fee from me to cover the costs incurred for the creation of the work, depending on the circumstances up to their actual amount.

I acknowledge that in accordance with Section 47b of Act No. 111/1998 Sb., On Higher Education Institutions and on Amendments to Other Acts (Act on Higher Education Institutions), as amended, and the Directive of the University of Pardubice No. 7/2019 Rules for Submission, Publication and Layout of Theses, as amended, the thesis will be published through the Digital Library of the University of Pardubice.

In Pardubice On 19.8.2025

Mohammad Abu Asad

GRATITUDE

I would like to thank my supervisor Ing. Jan Pokorný, Ph.D. for the great help, guidance, and advice he had provided throughout my work on this thesis.

ABSTRACT

Traffic evaluation using camera recordings has become an essential component of modern transportation engineering and accident reconstruction analysis. This thesis presents a comparative methodology for analysing vehicle dynamics through video-based assessment using Virtual Crash 6 (VC6) object tracking capabilities against high-precision Global Navigation Satellite System with Real-Time Kinematic (GNSS-RTK) technology as a reference standard.

The research employs VC6's advanced video analysis tools, including automatic object tracking, camera calibration, and motion measurement features, to extract vehicle trajectory and speed data from camera recordings at the Pardubice University junction. The VC6 system utilizes computer vision algorithms built on OpenCV framework, enabling automatic detection and tracking of vehicles through calibrated camera systems without requiring manual initialization or complex setup procedures.

The research contributes to the validation of video-based traffic analysis methods against established high-precision measurement standards, offering insights into the practical applications and limitations of camera-based traffic evaluation systems.

KEYWORDS

camera recordings, Virtual Crash 6, vehicle dynamics measurement, GNSS-RTK, traffic analysis, object tracking, accident reconstruction, motion measurement, video analysis, comparative measurement technology, computer vision, OpenCV, camera calibration, intersection analysis

ABSTRAKT

Vyhodnocování dopravy pomocí záznamů z kamer se stalo nezbytnou součástí moderní dopravní techniky a analýzy rekonstrukce nehod. Tato práce představuje srovnávací metodiku pro analýzu dynamiky vozidel prostřednictvím video-založeného hodnocení s využitím funkcí sledování objektů Virtual Crash 6 (VC6) ve srovnání s vysoce přesnou technologií Global Navigation Satellite System with Real-Time Kinematic (GNSS-RTK) jako referenčním standardem.

Práce využívá pokročilé nástroje pro analýzu videa VC6, včetně automatického sledování objektů, kalibrace kamery a měření pohybu, k extrakci dat o trajektorii a rychlosti vozidel z kamerových záznamů na křižovatce u Univerzity Pardubice. Systém VC6 využívá algoritmy počítačového vidění postavené na frameworku OpenCV, které umožňují automatickou detekci a sledování vozidel pomocí kalibrovaných kamerových systémů bez nutnosti ruční inicializace nebo složitých nastavovacích procedur.

Práce přispívá k ověření metod analýzy dopravy založených na videu ve srovnání se zavedenými vysoce přesnými měřicími standardy a nabízí vhled do praktických aplikací a omezení kamerových systémů pro hodnocení dopravy.

KLÍČOVÁ SLOVA

kamerové záznamy, Virtual Crash 6, měření dynamiky vozidel, GNSS-RTK, analýza dopravy, sledování objektů, rekonstrukce nehod, měření pohybu, analýza videa, srovnávací měřicí technologie, počítačové vidění, kalibrace kamery, analýza křižovatky

Content

1 INTRODUCTION

The accurate measurement and analysis of vehicle dynamics from video recordings represents a critical challenge in contemporary traffic engineering and accident reconstruction. As traffic complexity increases and the demand for precise incident analysis grows, the development of reliable, cost-effective methods for extracting vehicle motion parameters from visual data has become increasingly important.

Traditional approaches to traffic analysis have relied heavily on specialized measurement equipment, including radar systems, lidar sensors, and high-precision GNSS instrumentation. While these methods provide excellent accuracy, they are often expensive, require complex installation procedures, and may not be readily available for post-incident analysis when only camera recordings exist.

The emergence of sophisticated video analysis software, particularly Virtual Crash 6 (VC6), has created new opportunities for comprehensive traffic evaluation using camera recordings. VC6 represents a significant advancement in computer vision-based traffic analysis, offering automatic object tracking, camera calibration, and motion measurement capabilities that can extract detailed vehicle dynamics information from video footage.

This research addresses the fundamental question of how effectively video-based analysis using VC6 can replicate the accuracy of traditional high-precision measurement methods. By conducting a systematic comparison between VC6's object tracking capabilities and Global Navigation Satellite System with Real-Time Kinematic (GNSS-RTK) technology, this study aims to quantify the reliability and accuracy of camera-based traffic evaluation methods.

2 BASIC INFORMATION ABOUT IMAGE AND VIDEO RECORDING.

2.1 INTRODUCTION ABOUT IMAGE AND VIDEO RECORDING

To understand image and video recording, we have to go back to what the images are and to the basics of how we see things.

Vision or everything we see is the reflection of light that hits the objects we see. [1]

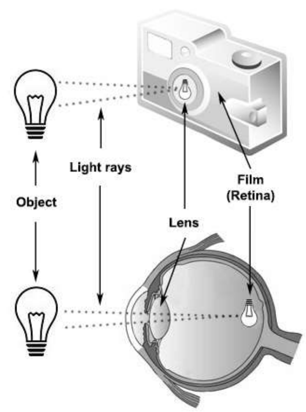

Figure 1 Demonstration of the concept of vision. [2]

In order to understand more we need to know what light is. Light is a beam of photons emitted from the light source (sun, lamp, etc.), this happens when the electrons of certain atoms is being excited – in the case of light bulb the tungsten wire is excited by a current of electricity which excites the electrons in the atoms - this is a temporary status, in such that the electrons then return to their original level of energy where they were, when they return to the stable state they emit the energy they've got during the process, - since energy cannot be created nor destroyed but changes from form to another - this energy is emitted as photons that can travel as electromagnetic waves. [1]

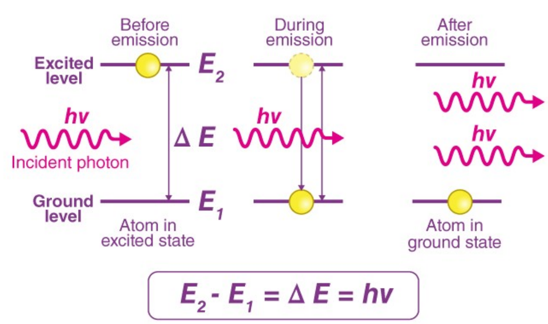

Figure 2 The concept of photon emission. [3]

Electromagnetic waves have a wide range of waves starting from the radio waves through the visible light all the way to gamma rays. The longer is the wavelength the less energy the wave has and the smaller the frequency of the wave. The visible light is between wavelengths from 380 nm to

700 nm. Every colour has various wavelength, which means different energy. Understanding that the things we see is energy is crucial to lay the foundation of the invention of cameras and image recording. [1]

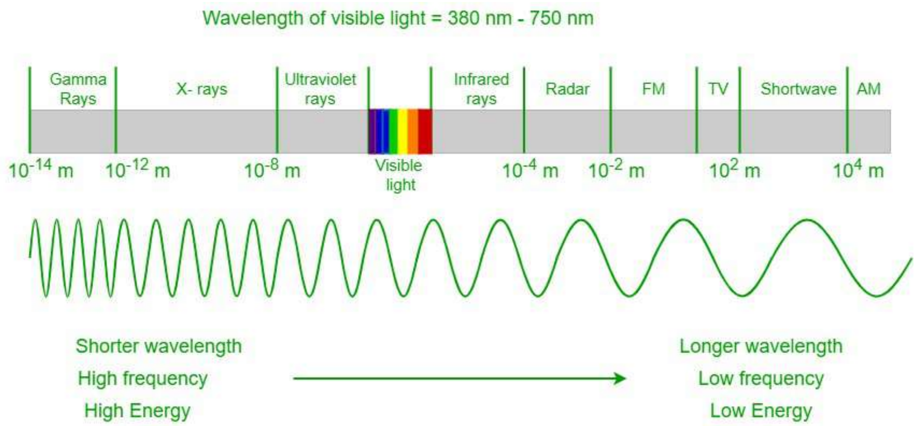

Figure 3 Electromagnetic spectrum. [4]

In the early stages of developing lenses in the past, Johann Heinrich Schulze, a German scientist, conducted a series of experiments in 1727, during the initial phases of lens development. In his published findings, Schulze revealed that the darkening of the salts occurred solely as a result of light. As a result and after further investigating light sensitive materials together with the early work of Ibn al-Haytham on pinhole and focal length findings, the first simple method of camera was developed. The light entered through a tiny hole a dark chamber that had at the end the light sensitive film. [1]

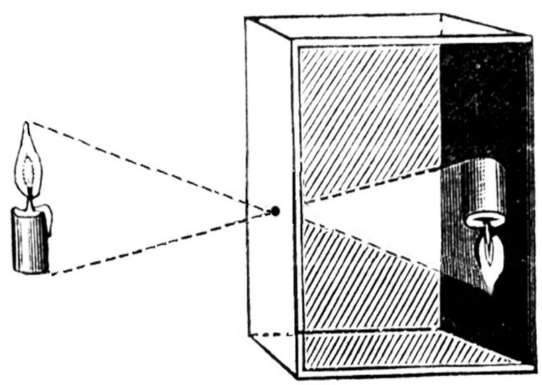

Figure 4 illustration of pinhole projection discovered by Ibn Al-Haytham [5]

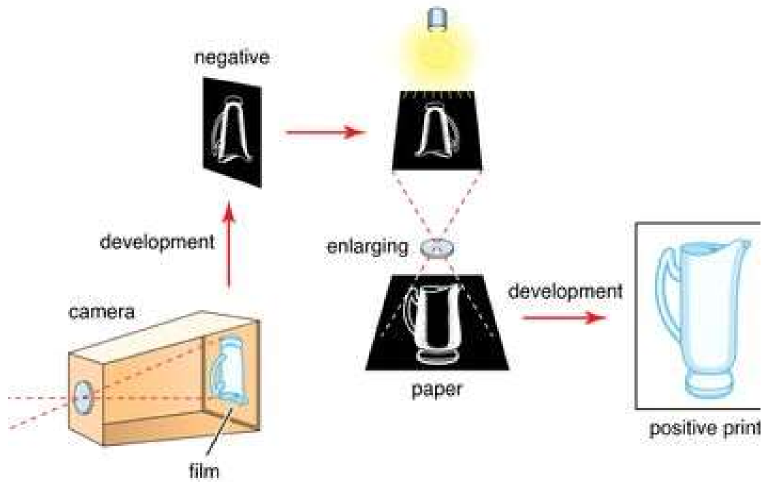

Figure 5 Basic Camera principle. [6]

Nowadays cameras work with the same principle, light is gathered using a lens the light is passes through an aperture all the way on the sensor. The sensor is made of light sensitive material that releases electrical current when light hits it. The sensor is structured in a matrix manner called pixels, each pixel will emit different current depending on the light colour and intensity (brightness), this then needs to be processed in the processor which should be calibrated for defined electrical energy the respective colour. This then is saved as some data matrix, in the memory and that’s how we can show it and transfer it from unit to another. [1]

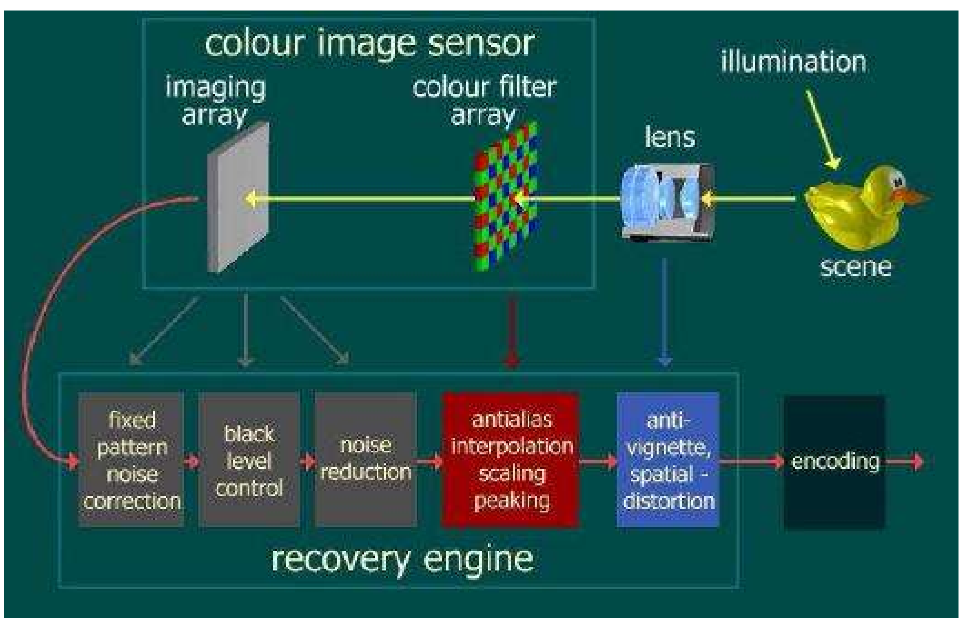

Figure 6 The principle of digital image capturing [7]

The video recording is not much different, since in the early stages it needed the film to constantly be moving in a constant speed so that on each frame is a single picture but it’s continuous so when then is projected it appeared to the viewer live, the speed of which the film was moving is called the frame rate. In modern cameras it is the same thing, since the camera sensor will take continuous shots (bursts) in a constant rate, which is the frame rate, a typical cinematic frame rate is 24 frames per second (fps). [1]

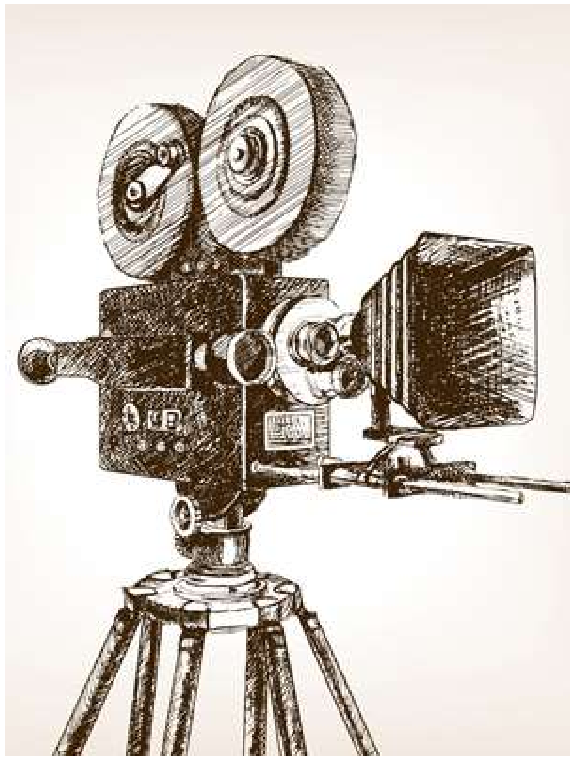

Figure 7 Earlier video camera illustration [8]

2.2 ELEMENTS AND PARAMETERS OF IMAGE AND VIDEO RECORDINGS

2.2.1 STORAGE UNITS

Whether it is from Micro SD cards to the huge data lakes it's essential to save the digital recording on some hardware capable of recalling it when reading the recording is needed. This will depend on the recording device, the recorded material, the quality desired, the frequency of recalling the recordings, etcs. From the often-used storages are:

- Hard drives (connected or offline with serves)
- CDs and DVDs
- SD cards

It's important to take into account the write and read speeds of the chosen storage since for example: SD cards come with various classes and depending on each class you will get a different write and read speed.

2.3 DEFINITION AND BASIC PRINCIPLES OF PHOTOGRAPHY

2.3.1 FOCAL LENGTH

Focal length represents the distance in millimeters between the point where light rays converge in a lens (nodal point) and the camera's sensor or film plane. This measurement is determined when the lens is focused at infinity, serving as the primary descriptor of a camera lens. [14]

When light passes through a lens, the focal length determines several key aspects of the resulting image:

- Field of View: Shorter focal lengths capture wider scenes, while longer focal lengths provide narrower views.
- Depth of Field: Longer focal lengths typically produce shallower depth of field, enabling focused capture of distant objects.
- Perspective: The focal length influences spatial relationships, with shorter lengths expanding perspective and longer lengths compressing it.

The focal length determines the classification of lenses:

- Wide-angle lenses (Macro): Characterized by short focal lengths.
- Telephoto lenses: Feature longer focal lengths.
- Standard lenses: Fall between these extremes. [14]

Nowadays smartphones come with such combination, for example the recent Iphone 15 pro has three rear lenses:

1- Wide angle (used as the standard) with 26 mm focal length.
2- Telephoto 77 mm for zooming (up to x3 optical zoom).
3- Ultra-wide angel lens also used for macro with 13 mm.

Figure 8 iphone 15 pro rear camera set. [15]

The relationship between object distance and focal length produces distinct imaging effects:

- Objects beyond twice the focal length produce inverted, smaller images.
- Objects at exactly twice the focal length create same-size inverted images.
- Objects between one and two focal lengths generate larger inverted images.

Figure 9 An illustration of different focal lengths from the right 24 mm, 35 mm, 55mm, 80 mm, 105 mm, 200m the photo was captured from the same spot and the zooming is due to optical effect

The focal length significantly impacts image characteristics:

- Magnification increases with longer focal lengths
- Angle of view narrows as focal length increases
- Image stabilization becomes more critical with longer focal lengths

2.3.2 APERTURE

It represents the opening gate? in a camera lens through which light passes to enter the camera. The aperture functions similarly to the human eye's pupil, expanding or contracting to control the amount of light reaching the camera sensor. This adjustment is accomplished through a system of aperture blades that move synchronously to modify the opening size. The size of the aperture is measured in f-stops, where a lower f-stop number indicates a larger opening and more light entry, while a higher f-stop number means a smaller opening and less light entry. [16]

Figure 10 Illustration of aperture effect on image [17]

Figure 11 illustration of different apertures from the right f1,7, 4,5, 6,3, 9, 14, 22 with 50 mm lens

Note that f1,7 has the portrait effect so only it focuses on the area of interest, in the contrast f22 has a large depth of field.

Figure 12 f1,7

Figure 13 f22 you can notice how clear is the background compared to the front most object (plant)

Effects on Photography

Exposure Control

The primary function of aperture is controlling the amount of light that reaches the camera sensor, directly affecting the image's exposure. In low-light conditions, a larger aperture allows more light to enter, while in bright environments, a smaller aperture helps prevent overexposure. [16]

Depth of Field

Aperture significantly influences the depth of field in photographs. A wide aperture (low f-stop) creates a shallow depth of field, which is particularly useful for portrait photography as it produces a blurred background effect. Conversely, a narrow aperture (high f-stop) results in a deeper depth of field, making it ideal for landscape photography where sharpness throughout the image is desired. [16]

Bokeh Quality

The aperture blades contribute to the aesthetic quality of the out-of-focus areas, known as bokeh. Lenses with more aperture blades typically produce rounder and more pleasing bokeh effects. [16]

Optimal Usage

Most lenses achieve maximum sharpness at apertures between f/8 and f/11. However, the choice of aperture should be based on the specific requirements of the photograph, considering factors such as available light, desired depth of field, and creative intent. [16]

2.3.3 SHUTTER SPEED

Shutter speed represents the duration for which a camera's shutter remains open, exposing the sensor to light. This fundamental aspect of photography controls both exposure and motion capture, making it a crucial element in image creation. [18]

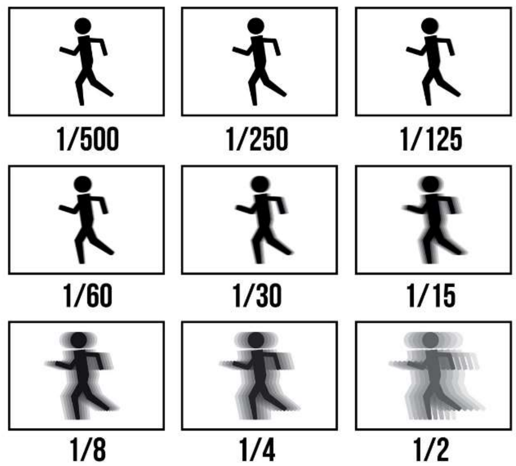

Figure 14 Illustration of the effect of different shutter speeds on capturing a moving object [19]

The shutter mechanism consists of a curtain positioned in front of the camera sensor that opens and closes during exposure. Modern cameras typically offer shutter speeds ranging from 1/8000th of a second to 30 seconds. Some newer models incorporate electronic shutters alongside mechanical ones, operating on the same principle but controlling exposure electronically. Phones and mirrorless cameras don't use a mechanical shutter, that's how they achieve a very small shutter speed up to 1/24000th of a second. [18]

EFFECTS ON IMAGE CREATION

1- **Exposure Control**
Shutter speed directly influences image brightness. Longer exposures allow more light to reach the sensor, resulting in brighter images, while shorter exposures produce darker results. This relationship makes shutter speed a vital tool for exposure management, particularly in varying lighting conditions. [18]

2- **Motion Capture**
The duration of exposure significantly affects how movement appears in photographs, fast shutter speed less than 1/1000th second, almost freezes moving objects, making it ideal for sports and wildlife photography. On the other hand, slow shutter speeds (more than 1/30th second) can make the moving objects blurrier, but it's very useful to get more light, making it ideal for capturing still objects with low light and no room for other parameters to be adjusted, like space shooting. [18]

TECHNICAL CONSIDERATIONS

1- **Handheld Photography**
Camera shakes become a significant concern with slower shutter speeds. A general rule suggests avoiding shutter speeds slower than the reciprocal of the lens focal length (e.g., 1/50th second for a 50mm lens). [18]

2- **Light Compensation**
   Shutter speed adjustments often require compensatory changes in aperture or ISO settings to maintain proper exposure. This interrelationship forms part of the exposure triangle, fundamental to photographic technique. [18]

2.3.4 ISO

ISO in photography represents one of the fundamental elements of exposure control, determining the sensitivity of a camera's sensor or film to light. This standardized measurement system plays a crucial role in achieving proper exposure alongside aperture and shutter speed. ISO functions as a measure of the camera sensor's sensitivity to light. When photographers increase the ISO setting, they effectively make the sensor more responsive to available light, resulting in brighter images. Below is the pros and cons of using low ISO and higone on image quality:

1- **Low ISO settings**
   Lower ISO settings (typically 100-400) produce the highest image quality with minimal noise. These settings are ideal for well-lit conditions and deliver:
   - clearer, sharper images,
   - better color accuracy,
   - enhanced dynamic range (distinguish the bright and dark area clearly in the picture).

2- **High ISO Settings**
   While higher ISO settings enable photography in low-light conditions, they introduce several compromises:
   - increased digital noise or grain,
   - reduced color accuracy,
   - diminished dynamic range,
   - limited post-processing flexibility.

The selection of ISO settings varies depending on lighting conditions and photographic requirements:

1- ISO 100: Optimal for bright, sunny outdoor conditions
2- ISO 400: Suitable for cloudy days or indoor photography near windows
3- ISO 800: Appropriate for indoor photography without additional lighting
4- ISO 1600 and above: Necessary for low-light situations requiring faster shutter speeds

You have to take into consideration that with higher ISO selection the picture will be grainy and sometimes might have some greenish dots because of the sensitivity that the sensor is set to have, as a rule of thumb know your camera's real limit of ISO and try to limit your shooting to that limit when capturing, the camera might offer a very high ISO like 32 000 but the actual limit that you can use without noise is 1600, knowing that you can set the auto ISO range to be limited to 1600 or 3200, the ISO setting always doubles, so 100, 200, 400, 800 and so on. [20]

2.3.5 Sensors, sensor sizes, crop ratio

Digital camera sensors come in various sizes, significantly impacting image characteristics and photographic capabilities. The relationship between sensor sizes and their effects on photography is primarily expressed through the concept of crop factor.

Figure 15 Comparison chart of different camera sensor size [25]

SENSOR SIZES AND CLASSIFICATIONS

- **Full-Frame Sensors**

The full-frame sensor, measuring 36×24mm, serves as the industry standard reference, equivalent to traditional 35mm film format1. This sensor size has a crop factor of 1.0, providing the baseline for comparing other sensor formats. Example of cameras with full frame sensors include Sony alpha 7 IV and the Canon 5d IV.

Figure 16 Sony alpha 7 IV with full-frame sensor [22]

- **APS-C Format**

APS-C sensors represent a common format in consumer-level cameras, with slight variations among manufacturers:

- Nikon, Sony, and Fujifilm utilize 23.6×15.6mm sensors with a 1.5x crop factor
- Canon implements a slightly smaller 22.2×14.8mm sensor with a 1.6x crop factor

Figure 17 Canon R10 with APS-C sensor [23]

- **Micro Four Thirds**

The Micro Four Thirds system, adopted by manufacturers like Panasonic and OM System (formerly Olympus), features a sensor size of 17.3×13mm with a 2.0x crop factor.

Figure 18 OM E-M10 Mark IV with 4/3 sensor [24]

Crop Factor Calculation

The crop factor is mathematically determined by comparing sensor diagonals to the full-frame diagonal. The formula is:

$$crop\ factor = \frac{Full\ frame\ diagonal}{Sensor\ diagonal}$$

For example, calculating the crop factor of the APS-C (23,6 x 15,6 mm) as follows:

$$Full\ frame\ diagonal = 43{,}27\ mm$$
$$APS - C\ diagonal = \sqrt{23{,}6^2 + 15{,}6^2} = 28{,}29\ mm$$
$$Crop\ factor = \frac{43{,}27}{28{,}29} \approx 1{,}5$$

IMPACT ON PHOTOGRAPHY

1- Field of View

The crop factor directly affects the effective focal length of lenses. A 50mm lens mounted on a camera with a 1.5x crop factor provides a field of view equivalent to a 75mm lens on a full-frame camera.

2- Depth of Field

Sensor size influences depth of field characteristics. Smaller sensors generally produce greater depth of field at equivalent focal lengths and apertures. For instance, Micro Four Thirds cameras with their 2x crop factor exhibit approximately twice the depth of field compared to full-frame cameras under similar conditions. [21]

2.3.6 FRAME RATE

Frame rate, a critical parameter in both still and motion photography, governs the temporal resolution and visual continuity of captured sequences. This comprehensive analysis examines frame rate's technical foundations, historical evolution, diverse applications across industries, and emerging trends shaping its future. By synthesizing insights from foundational photographic literature, contemporary research, and international standards, this report elucidates how frame rate interacts with sensor technology, storage systems, and creative objectives. Key findings reveal that while standard video employs 24–60 fps for human perceptual continuity, specialized applications demand extremes from 10^6 fps in scientific imaging to sub-1 fps in astrophotography, each presenting unique technical trade-offs[26][27][28].

TECHNICAL FOUNDATIONS OF FRAME RATE

1.1 Definition and Measurement

Frame rate quantifies the number of individual images (frames) captured or displayed per second, expressed in frames per second (fps). The International Organization for Standardization defines it as "the temporal frequency at which consecutive images are recorded or rendered"3. Measurement involves either:

1. **Direct sensor readout**: Counting completed exposure cycles via CMOS or CCD clock signals.
2. **Post hoc analysis**: Calculating $\frac{\text{Total Frames}}{\text{Recording Duration}}$ through timestamp metadata [27].

1.2 Physical and Computational Constraints

Achieving target frame rates requires balancing:

- **Shutter mechanics**: Rotary shutters in film cameras physically limit fps to 1/1000 s intervals, whereas digital global shutters enable ≥ 10^5 fps through electronic gating [26].
- **Sensor readout speed**: Pixel array scanning rates, governed by analog-to-digital converter (ADC) throughput, create an inverse relationship between resolution and fps (fps∝1/Resolution)[28].
- **Thermal management**: High-speed imaging generates sensor heat, necessitating active cooling to prevent dark current noise from exceeding signal thresholds[27].

HISTORICAL EVOLUTION OF FRAME RATE CAPABILITIES

2.1 Analog Era (1839–1990)

Early photographic processes like daguerreotypes (1839) achieved ≈0.004 fps (15-minute exposures), progressing to:

- **Chronophotograph**: Eadweard Muybridge's 1878 horse motion studies at 12 fps using multi-camera setups
- **Cinematic film**: Standardized 24 fps established by 1927's *The Jazz Singer* to synchronize sound[26].

2.2 Digital Revolution (1990–2020)

CMOS sensor adoption enabled programmable frame rates, with milestones including:

- 1999: First 1,000 fps consumer camera (Casio QV-770UX)
- 2012: Phantom Flex4K reaching 1,000 fps at 4K resolution
- 2020: Sony's IMX636 sensor achieving 40,960 fps via pixel binning[28].

FRAME RATE APPLICATIONS ACROSS INDUSTRIES

3.1 Cinematography and Broadcast

While 24 fps remains the cinematic standard for its "film look," broadcast environments employ:

- **50/60 fps**: PAL/NTSC television compatibility
- **120+ fps**: High dynamic range (HDR) and virtual reality (VR) content to reduce motion blur during head movements[27].

3.2 Scientific and Industrial Imaging

Extreme frame rates facilitate phenomena analysis at microsecond scales:

- **Ballistics**: Tracking bullet deformation at 10^6 fps
- **Fluid dynamics**: Capturing shockwave propagation in supercooled helium[28].

CHALLENGES IN HIGH-SPEED PHOTOGRAPHY

4.1 Data Throughput Limitations

A 10-megapixel sensor at 1,000 fps generates: 10×10^6 pixels frame × 10^3 fps × 14 bits pixel = 1.4×10^{11} bits s. Requiring PCIe 4.0 x16 interfaces (31.5 GB/s) for uncompressed capture[28].

4.2 Exposure Trade-Offs

The exposure time per frame t_{exp} must satisfy:

$$t_{exp} \leq \frac{1}{fps} - t_{readout}$$

Where $t_{readout}$ is sensor scanning time, forcing high fps sequences to use wider apertures or higher ISO settings, increasing noise[26].

FUTURE TRENDS AND INNOVATIONS

5.1 Compressive Sensing Techniques

Machine learning algorithms like convolutional neural networks (CNNs) enable:

- **Frame interpolation**: Generating 240 fps output from 60 fps input via motion vector prediction
- **Bandwidth reduction**: 10:1 compression ratios while maintaining temporal fidelity [27].

5.2 Quantum Image Sensors

Single-photon avalanche diode (SPAD) arrays promise:

- **Picosecond resolution**: Time-correlated single-photon counting for 10^{12} fps
- **Photon efficiency**: Imaging in 0.001 lux conditions without gain [28].

Frame rate selection remains a critical compromise between temporal resolution, light sensitivity, and storage capacity across photographic applications. As sensor readout speeds approach fundamental physical limits, future advancements will likely prioritize computational photography and quantum detection to bypass traditional fps constraints.

3 MACHINE LEARNING INTRODUCTION

Machine Learning has emerged as a pivotal branch of Artificial Intelligence (AI), driven by the fundamental challenge of creating intelligent systems. While traditional programming excels at specific algorithmic tasks like pathfinding, many complex challenges such as speech recognition, medical diagnosis, and autonomous vehicle operation have proven resistant to explicit programming approaches. This limitation has led to the development of self-learning systems as the primary methodology for addressing sophisticated computational challenges. [9]

The field's evolution extends beyond immediate practical applications toward the ambitious goal of Artificial General Intelligence (AGI), though this remains a distant prospect despite significant technological advances. The machine learning approach, particularly neural network architectures inspired by biological systems, has emerged as the predominant pathway toward enhanced artificial intelligence capabilities. [9]

The economic implications of machine learning are substantial, with projections indicating a potential annual value creation of $13 trillion by 2030. While the technology sector has already witnessed significant transformation through machine learning applications, numerous traditional industries including retail, transportation, manufacturing, and automotive sectors present untapped opportunities for revolutionary advancement. This vast potential has created unprecedented demand for machine learning expertise across diverse economic sectors. [9]

Machine Learning is defined as the field of study that enables computers to learn without explicit programming, a concept first articulated by Arthur Samuel in the 1950s. This definition was demonstrated through Samuel's pioneering checkers program, which achieved mastery through iterative self-play, analyzing winning and losing positions across thousands of games until surpassing human expertise. [9]

Machine Learning encompasses three primary domains: supervised learning, unsupervised learning, and recommender systems. Among these, supervised learning has emerged as the most widely implemented category, driving significant technological advancement and practical applications across various sectors. This methodology has been instrumental in developing solutions for complex computational challenges where traditional programming approaches prove insufficient. [9]

The field's significance is particularly evident in its ability to address tasks that resist explicit algorithmic solutions, demonstrating remarkable efficacy in pattern recognition, data analysis, and autonomous decision-making processes. Through continuous refinement of learning algorithms, these systems can achieve increasingly sophisticated levels of performance in specialized domains. [9]

3.1 SUPERVISED MACHINE LEARNING

Supervised machine learning represents a categorical approach within artificial intelligence that facilitates the systematic learning of input-output (x-y) correlations. This methodology is predicated on the provision of exemplary datasets, where each input variable (x) is paired with its corresponding correct output label (y). Through iterative exposure to these validated pairs, the algorithm develops the capability to generate accurate predictions for novel, previously unencountered inputs.

The practical applications of supervised learning span diverse sectors. In digital communications, it enables spam detection through email content analysis. In linguistic applications, it facilitates both speech recognition and machine translation across multiple language pairs. The commercial sector, particularly online advertising, has witnessed significant revenue generation through supervised learning algorithms that predict user engagement probabilities based on advertisement characteristics and user profiles.

In the automotive industry, supervised learning algorithms process sensory inputs, including visual and radar data, to facilitate autonomous vehicle navigation through precise object positioning. Quality control in manufacturing benefits from visual inspection systems that analyze product imagery to detect manufacturing defects. These implementations demonstrate the versatility of supervised learning in processing complex, multi-modal inputs.

The fundamental operational principle involves initial model training using validated input-output pairs. Post-training, the model demonstrates generalization capabilities, processing novel inputs to generate appropriate outputs based on learned patterns. This methodology's success relies on the quality and representativeness of the training dataset and the algorithm's ability to extract meaningful patterns from these examples. [9]

3.1.1 Regression

Linear regression represents a foundational methodology within the supervised learning paradigm, specifically designed for numerical prediction tasks. This statistical approach operates within an infinite continuous output space, distinguishing it from discrete classification problems. Linear regression establishes a mathematical correlation between dependent (target) and independent (predictor) variables, predicated on the fundamental assumption of linearity in their relationship. The methodological framework rests upon several critical statistical presumptions:

1- **Linearity**: The relationship between the input features and output variable is assumed to be linear.
2- **Independence**: Each data point is independent of others (no correlations).
3- **No multicollinearity**: Features should not be highly correlated with each other.

In its simplest univariate form, the model examines the relationship between a single predictor variable (x) and the target variable (y). The primary objective is to determine an optimal linear function that minimizes the disparity between predicted (ŷ) and observed (y) values, typically through the method of least squares estimation.

The linear regression model can be represented by the following equation:

$$\hat{y} = \omega \cdot x + b$$

In order to find how far we are from the right value y, usually the Mean squared error (MSE) is used to help find the distance from it, this is called the Cost function.

The cost function $J(x)$ is defined as:

$$J(x) = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}_i - y_i)^2$$

Where:

- $\hat{y}$ is the predicted value.
- ω, b represents the parameters (weights) of the linear regression model.
- x is the input feature(s).
- m is the number of training examples.

These two equations help with model creation (initiation) and testing. For it to be trained we need to make the cost reach the small value (acceptable error), so we need to iterate through the value ω, b until this error reaches the best possible error (the smallest value), to do so, we use gradient decent and iterate it until it diverges the cost to minimum.

The gradient decent equation (in the programming from):

$$\omega \ = \omega - \alpha \cdot \left(\frac{\partial J}{\partial \omega}\right)$$

$$b \ = b - \alpha \cdot \left(\frac{\partial J}{\partial b}\right)$$

- α is the learning rate.
- $\frac{\partial J}{\partial \omega}$ and $\frac{\partial J}{\partial b}$ are the partial derivatives of the cost function with respect to each parameter.

The parameter optimization process necessitates spontaneous adjustments of weighted variables to ensure methodological integrity. This dynamic approach to parameter modification represents a crucial aspect of model training.

The relationship between training and testing error rates serves as a critical indicator of model performance. A fundamental principle in statistical learning suggests that error metrics should maintain consistency across both training and testing datasets. Significant divergence between these error rates—specifically, low training error coupled with elevated testing error—indicates the presence of high bias in the model.

This statistical condition, wherein the model demonstrates superior performance on training data but fails to generalize effectively to novel datasets, is characterized as overfitting. Such a phenomenon represents a fundamental challenge in machine learning, indicating excessive model specialization to training data patterns at the expense of generalization capability.

These considerations underscore the importance of maintaining balanced model optimization, where the objective extends beyond merely minimizing training error to ensure robust performance across diverse data samples. This approach aligns with the broader principles of statistical learning theory and model validation methodology.

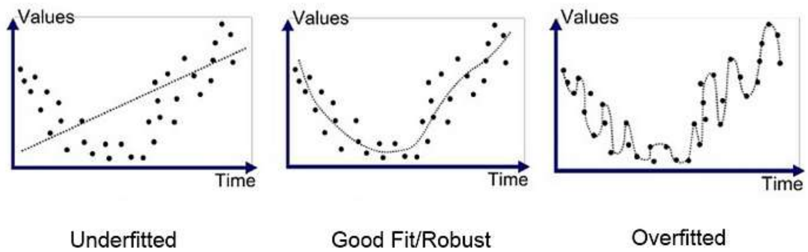

Figure 19 Example of underfitting/good fitting/ overfitting regression models for the same dataset

Below is a plot of some sample data for house prices with one parameter which is the size and the prediction of the price after making a linear regression model in the left, in the right is the plot of a small map of various ω and b values, and below is the cost function for both parameters ω, b.

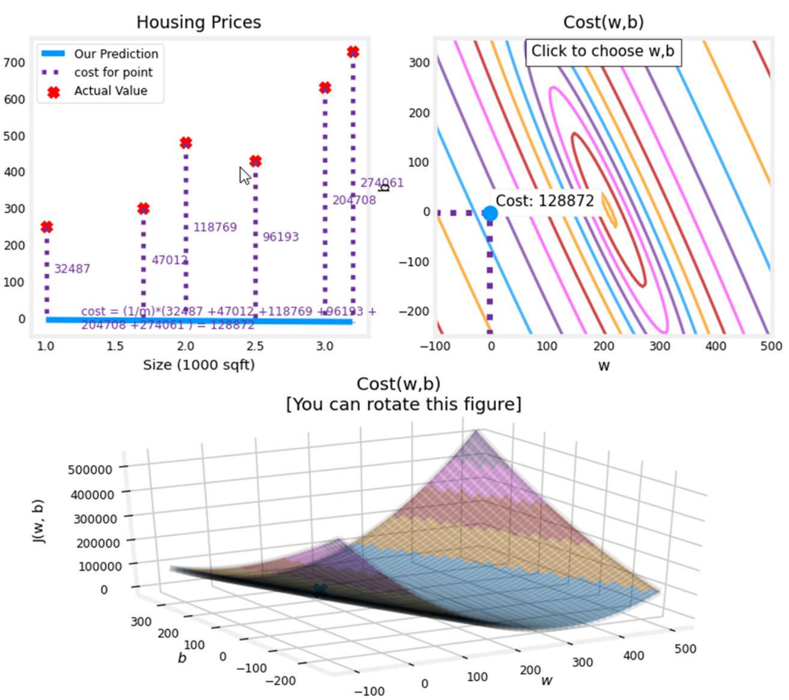

Figure 20 an example when initial parameters are 0.

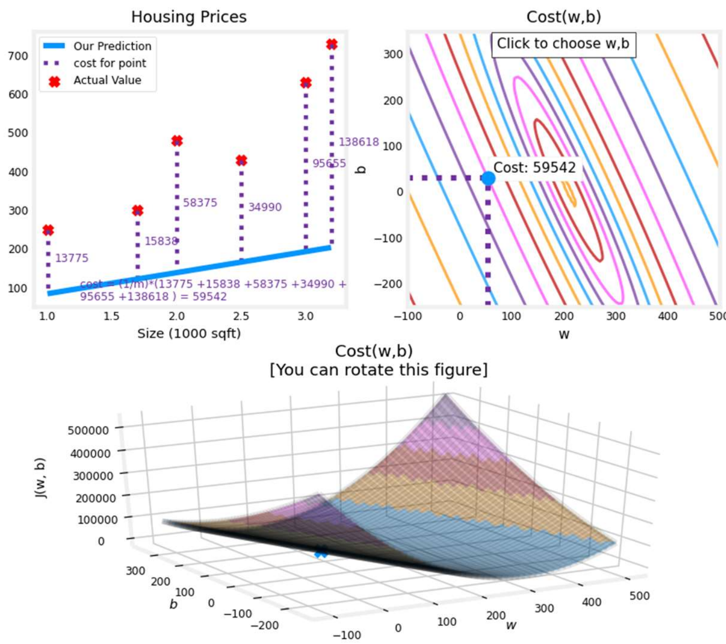

Figure 21 when the parameters are underfitting the data.

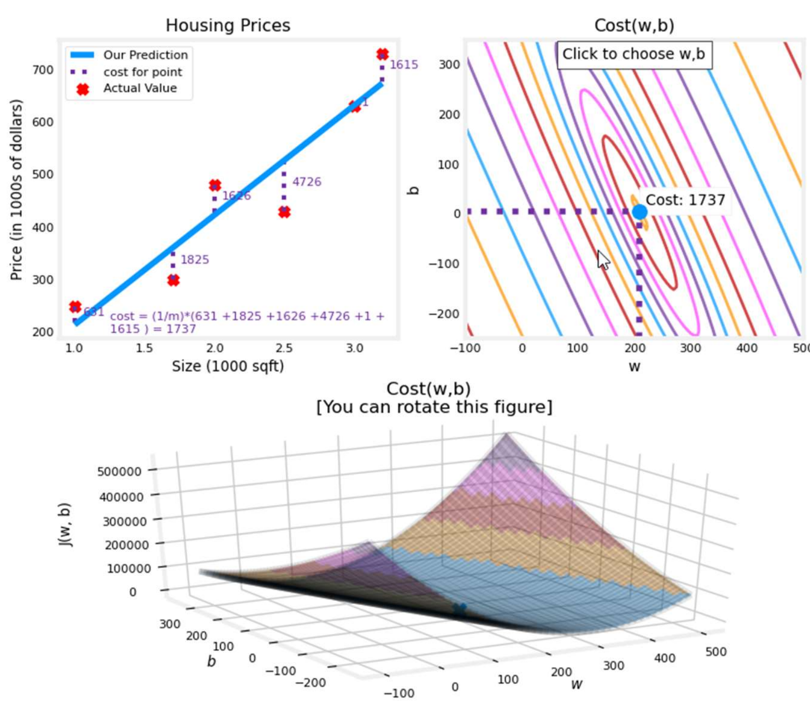

Figure 22 an example where after iterations we got a better model that still has a high cost but it fits well the model.

As we can see the more we diverge to a lower cost we get a better model that fits the parameters better. The cost still not good but in this case we can add more parameters for our training data, in this particular example we can add the number of rooms, the age of the house to help the model achieve a better result but in that case the model might net stay linear. The example is very simplified for the purpose of explaining. The program used to plot the graphs is Jupyter notebook using python scripts. [9] [11]

3.1.2 CLASSIFICATION

There's a second major type of supervised learning algorithm called a classification algorithm. this is different from regression is that we're trying to predict only a small number of possible outputs or categories. This is different from regression which tries to predict any number, all of the infinitely many number of possible numbers. And so the fact that there are only two possible outputs is what makes this classification. Because there are only two possible outputs or two possible categories, in classification problems you can also have more than two possible output categories. In classification, the terms output classes and output categories are often used interchangeably. So to summarize classification algorithms predict categories. Categories don't have to be numbers. It could be non numeric for example, it can predict whether a picture is that of a cat or a dog. And it can predict if a tumor is benign or malignant. Categories can also be numbers like 0, 1 or 0, 1, 2. But what makes classification different from regression when you're interpreting the numbers is that classification predicts a small finite limited set of possible output categories such as 0, 1 and 2 but not all possible numbers in between like 0.5 or 1.7.

LOGISTIC REGRESSION

Logistic regression is probably the single most widely used classification algorithm in the world. It is a statistical method used for binary classification problems, where the outcome variable is categorical with two (usually) possible outcomes. It models the probability that a given input point belongs to a particular class. For example, whether a certain image is 0 or not, if a certain parameter is ok/nok as an output. To do so usually we use the following set of equations, first the input parameters are inputted in a linear combination of the input features:

$$z = \omega \cdot x + b$$

- z is the linear combination.
- ω, b represents the parameters (weights) of the model.
- x is the input feature(s).

Next, we need to input this linear combination to the sigmoid function as in the following:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

- $\sigma(z)$ is the probability output between 0 and 1

Then the output $\sigma(z)$ is being categorized to each category upon a threshold. Below is a set of generated data between -10 and 10 evenly spaced and it’s sigmoid z and $\sigma(z)$:

z	$\sigma(z)$

-1.000E+01	4.540E-05
-9.000E+00	1.234E-04
-8.000E+00	3.354E-04
-7.000E+00	9.111E-04
-6.000E+00	2.473E-03
-5.000E+00	6.693E-03
-4.000E+00	1.799E-02
-3.000E+00	4.743E-02
-2.000E+00	1.192E-01
-1.000E+00	2.689E-01
0.000E+00	5.000E-01
1.000E+00	7.311E-01
2.000E+00	8.808E-01
3.000E+00	9.526E-01
4.000E+00	9.820E-01
5.000E+00	9.933E-01
6.000E+00	9.975E-01
7.000E+00	9.991E-01
8.000E+00	9.997E-01
9.000E+00	9.999E-01
1.000E+01	1.000E+00

Table 1 Sample data for a logistic regression model

If we plot the data in a graph and by defining the threshold to be 0 and each side of the threshold with a different color, we get this graph:

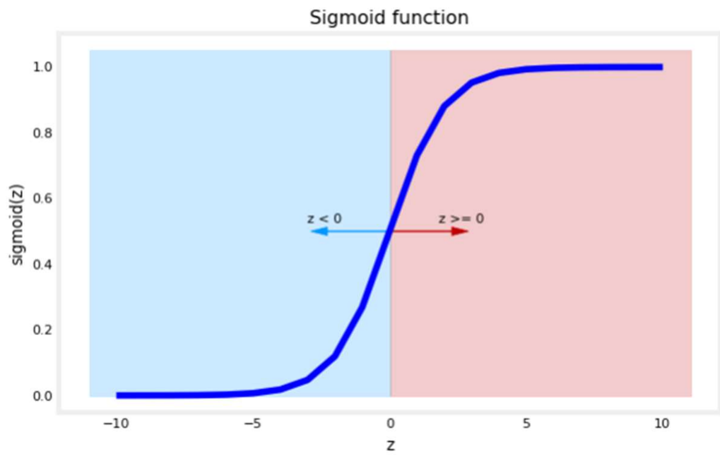

Figure 23 plot of sigmoid function threshold = 0

Note that in this example we set the threshold (decision boundary to be 0) this can be decided otherwise depending on the dataset. If the dataset was depending on more parameters x_1, x_2, x_n where each n is a parameter that the output is decided to be dependent on, then nothing changes to the function rather the change will be in the decision boundary as long as the goal is to have categories. For example let's suppose you have following training dataset:

x_0	x_1	y
0.5	1.5	0
1	1	0
1.5	0.5	0
3	0.5	1
2	2	1
1	2.5	1

Table 2 logistic regression sample data with multiple parameters

When we plot the data and assign when y = 0 as blue circles and y = 1 to be red x then we get this:

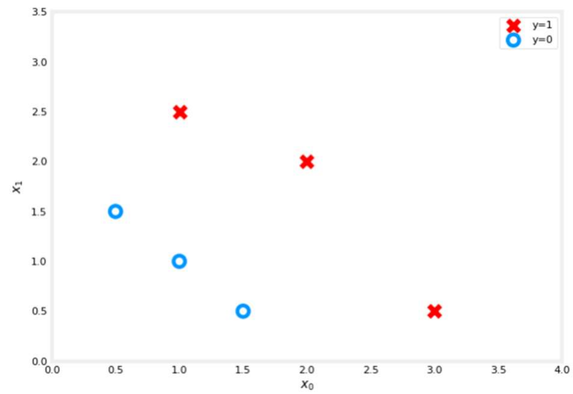

Figure 24 The plot of logistic regression sample data with multivariable

Clearly, we can see that for this sample data the decision boundary will look something like this:

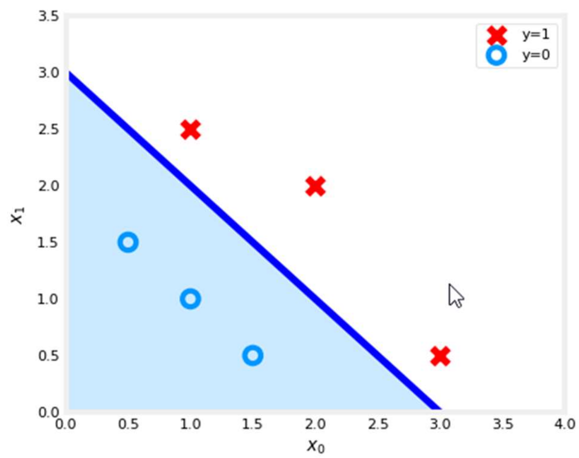

Figure 25 the plot of the decision boundary for multivariable logistic regression sample

To train the model and to verify how far we are from the right value and compare the model performance we use a similar approach to the linear regression model which is the cost function and the gradient decent. The catch here is that the result is between 0 and 1 but the real value is either 0 or 1 so we need to count for that so to implement that in the change of the cost function as the following:

$$J(\sigma(z), y) = -y \log\big(\sigma(z)\big) - (1 - y) \log\big(1 - \sigma(z)\big)$$

Where:

- $J(\sigma(z), y)$ is the cost function of the logistic regression
- y is the real value (output)
- $\sigma(z)$ is the predicted output (sigmoid)

To train the model we need repeatedly go through the different wights ω and b for all the parameters so that we achieve the lowest cost (error) to do so we loop through the values and simultaneous update the weights.

The gradient decent equation (in the programming from):

$$\omega = \omega - \alpha \cdot \left(\frac{\partial J}{\partial \omega}\right) = \omega - \alpha \cdot \left[\frac{1}{m}\sum_{i=1}^{m}\left(\sigma(z)^{(i)} - y^{(i)}\right) \cdot x^{(i)}\right]$$

$$b = b - \alpha \cdot \left(\frac{\partial J}{\partial b}\right) = b - \alpha \cdot \left[\frac{1}{m}\sum_{i=1}^{m}\left(\sigma(z)^{(i)} - y^{(i)}\right)\right]$$

- α is the learning rate.
- $\frac{\partial J}{\partial \omega}$ and $\frac{\partial J}{\partial b}$ are the partial derivatives of the cost function with respect to each parameter.

Little note here that all these equations don't to be implemented in your project every time from scratch, there are some well designed libraries open source and available for everybody to make their project without starting from nothing, such as Scikit-Learn to do so, you can just use such lines for example for logistic regression:

$from\ sklearn.linear\_model\ import\ LogisticRegression$

$lr\_model\ =\ LogisticRegression()$

$lr\_model.fit(X, y)$

Simply with these 3 lines you already can implement all what was said here about logistic regression and more, assuming you had defined y and X, note that X can be a multi parameter input.

Logistic regression is an essential tool that is used in more complicated machine learning methods like neural networks, which we will be talking about briefly later on. [9]

3.2 NEURAL NETWORK

When neural networks were first invented many decades ago, the original motivation was to write software that could mimic how the human brain or how the biological brain learns and thinks. Even though today, neural networks, sometimes also called artificial neural networks, have become very different than how any of us might think about how the brain actually works and learns. Some of the biological motivations remain in the way we think about artificial neural networks or computer neural networks today.

The human brain, or maybe more generally, the biological brain demonstrates a higher level or more capable level of intelligence and anything else would be on the bill so far. So neural networks have started with the motivation of trying to build software to mimic the brain. Work in neural networks had started back in the 1950s, and then it fell out of favor for a while. Then in the 1980s and early 1990s, they gained in popularity again and showed tremendous traction in some applications like handwritten digit recognition, which were used even backed then to read postal codes for writing mail and for reading dollar figures in handwritten checks. But then it fell out of favor again in the late 1990s. It was from about 2005 that it enjoyed a resurgence and became rebranded little bit with deep learning. Since then, neural networks have revolutionized application area after application area. The first application area that modern neural networks or deep learning, had a huge impact on was probably speech recognition, where we started to see much better speech recognition systems due to modern deep learning and authors such as [inaudible] and Geoff Hinton were instrumental to this, and then it started to make inroads into computer vision. Then the next few years, it made us inroads into texts or into natural language processing, and so on and so forth. Now, neural networks are used in everything from climate change to medical imaging to online advertising to product recommendations and really lots of application areas of machine learning now use neural networks.

Even though today's neural networks have almost nothing to do with how the brain learns, there was the early motivation of trying to build software to mimic the brain. So how does the brain work?

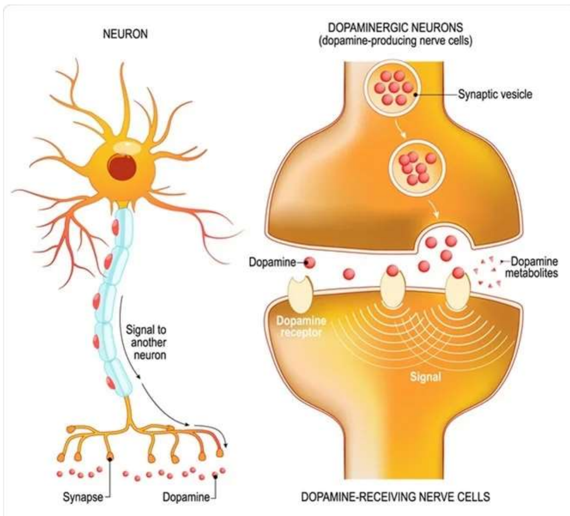

Figure 26 illustration of neurons in action

All of human thought is from neurons like this in the brain, sending electrical impulses and sometimes forming new connections of other neurons. Given a neuron like this one, it has a number of inputs where it receives electrical impulses from other neurons, and then this neuron that I've circled carries out some computations and will then send this outputs to other neurons by this electrical impulses, and this upper neuron's output in turn becomes the input to this neuron down below, which again aggregates inputs from multiple other neurons to then maybe send its own output, to yet other neurons, and this is the stuff of which human thought is made. In a biological neuron, the input wires are called the dendrites, and it then occasionally sends electrical impulses to other neurons via the output wire, which is called the axon. But this biological neuron may then send electrical impulses that become the input to another neuron. So the artificial neural network uses a very simplified Mathematical model of what a biological neuron does. What a neuron does is it takes some inputs, one or more inputs, which are just numbers. It does some computation and it outputs some other number, which then could be an input to a second neuron, shown here on the right. When you're building an artificial neural network or deep learning algorithm, rather than building one neuron at a time, you often want to simulate many such neurons at the same time.

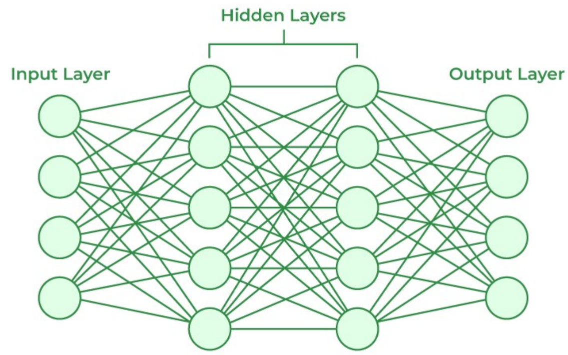

Figure 27 an illustration of how an artificial neural network looks in the logic of it

In this diagram, each circle represents a single neuron each column of neurons represents a layer. What these neurons do collectively is input a few numbers, carry out some computation, and output some other numbers. Just to clarify, even though we made a loose analogy between biological neurons and artificial neurons, I think that today we have almost no idea how the human brain works. In fact, every few years, neuroscientists make some fundamental breakthrough about how the brain works and we'll continue to do so for the foreseeable future, thus attempts to blindly mimic what we know of the human brain today, which is frankly very little, probably won't get us that far toward building raw intelligence. Certainly not with our current level of knowledge in neuroscience. Having said that, even with these extremely simplified models of a neuron, current neural networks and deep learning algorithms are really powerful algorithms. In this thesis, a prebuilt image processing CNN (convolutional neural network) algorithm is used to process the video recordings that later will be used.

Engineering principles to figure out how to build algorithms that are more effective rather than the biological motivation. There is a common a question between people, and you might wonder why only in the last handful of years that neural networks have really taken off? Data and computational power are the answer. Over the last couple of decades, with the rise of the Internet, the rise of mobile phones, the digitalization of our society, the amount of data we have for a lot of applications has steadily raised exponentially. Lot of records that used to be recorded on paper are not anymore, such as if you order something rather than it being on a piece of paper, there's much more likely to be a digital record. Your health record, if you see a doctor, is much more likely to be digital now compared to on pieces of paper. So, in many application areas, the amount of digital data has exploded. What was noticed with traditional machine-learning algorithms, such as logistic regression and linear regression, even as you fed those algorithms more data, it was very difficult to get the performance to keep on going up. So, it was as if the traditional learning algorithms like linear regression and logistic regression, they just weren't able to scale with the amount of data we could now feed it and they weren't able to take effective advantage of all this data we had for different applications. The bigger the neural network was built, the higher the performance was with big data. So this meant two things, it meant that for a certain class of applications where you do have a lot of data (big data) if you're able to train a very large neural network to take advantage of that huge amount of data you have, then you could attain performance on anything ranging from speech recognition, to image recognition, to natural language processing applications and many more, they just were not possible with earlier generations of learning algorithms. This caused deep learning algorithms to take off, and this too is why faster computer processors, including the rise of GPUs or graphics processor units. This is hardware originally designed to generate nice-looking computer graphics but turned out to be really powerful for deep learning as well. That was also a major force in allowing deep learning algorithms to become what it is today. That's how neural networks got started, as well as why they took off so quickly in the last several years.

To get an idea of how it's built let's just briefly shed the light on how it is made and then also give a prebuilt method to be used if you want to build your own.

Let's suppose we want to illustrate a neural network, we will draw each element so later the math can make since.

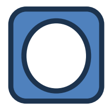

Figure 28 an element of neural network (NN) it is called a neuron

The group of these neurons in one stage is called a layer

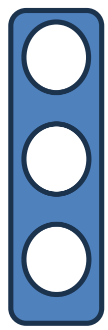

Figure 29 one layer of a NN with multi-neurons specifically here 3 neurons (3 parameters)

Let's now construct a simple NN with 3 layers where the first layer has an input parameter, and the output of it is the input of the next one and so on, until the last layer (the output layer) where the output of it is the result which might be the expectation, expected price, etc.

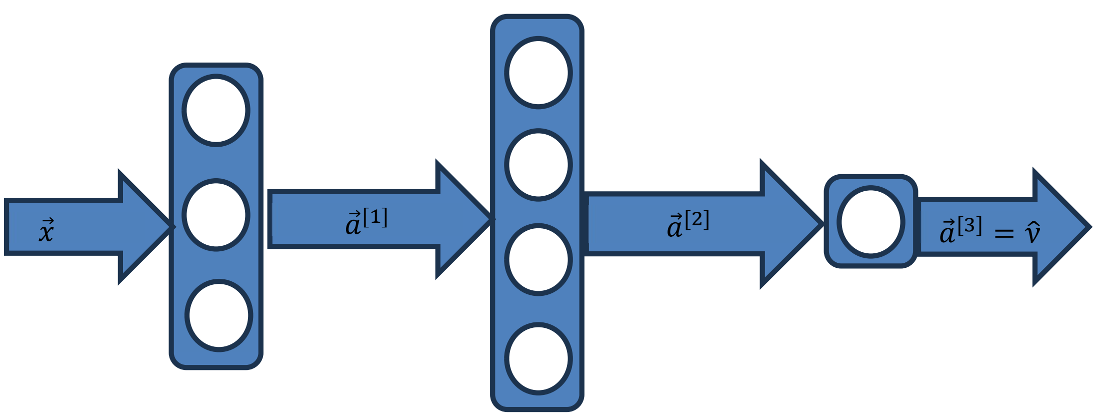

Figure 30 an illustration of a simple neural network

From the left to right, the first arrow illustrates all the input parameters (x_n) the first layer is called the input layer which has 3 neurons elements, the output of the first layer is called the activation of the next layer, and it's the input of the next layer, all the intermediate layers between the input and the output layer are called hidden layers, this hidden layer has 4 neurons, the second activator which is the output of the second layer (the hidden layer) is the input for the output layer of our simple neural network (NN). Finally, the output of this output layer is what we would expect as a result of our model, which is compared with the real values y.

This is all just the logic behind it, we are now going to shed the light on the math behind it. As we saw each layer can have multiple neurons, but each layer should have the same activation type, here we can recall our previous methods like logistic and linear regression. Apparently using these methods also in neural network is possible, but it's not the best option especially for the hidden layers.

For example if we consider the upper illustration and suppose that the activations that we decide to use are all logistic regression for this neural network, then the equation for the first layer can be like this:

$$\vec{a}^{[1]} = g\left(\vec{\omega}^{[1]} \cdot \vec{x} + \vec{b}^{[1]}\right)$$

This is the vector format of the equation, so it calculates the three neurons at once parallelly that's why GPUs (graphics processing units) come in when it comes to NN training. If we want to calculate it in a loop manner, we can use the following:

$$\vec{a}_1^{[1]} = g\left(\vec{\omega}_1^{[1]} \cdot \vec{x} + \vec{b}_1^{[1]}\right)$$

$$\vec{a}_2^{[1]} = g\left(\vec{\omega}_2^{[1]} \cdot \vec{x} + \vec{b}_2^{[1]}\right)$$

$$\vec{a}_3^{[1]} = g\left(\vec{\omega}_3^{[1]} \cdot \vec{x} + \vec{b}_3^{[1]}\right)$$

Where:

- $\vec{a}_m^{[n]}$ is the activation of the next layer n+1 for the m^{th} neuron in the n^{th} layer.
- $\vec{a}_m^{[n]} \dashrightarrow [n]$ is the layer number.
- $\vec{a}_m^{[n]} \dashrightarrow m$ is the neuron number.
- $g(z)$ is the sigmoid function of the parameters z.

The same logic is applied to calculate the other layers so to get the output (prediction) of the NN.

As we saw it's kind of time consuming and this can cause possibly error and it's harder to write than recalling a prebuilt libraries and well-constructed methods that you easily can implement to create you NN and to train it, one example is TensorFlow library. For this certain example we could use the following code in PY if you already had installed TensorFlow library. The following code can be tailored to your needs and be used to train such a NN, but with some things to keep in mind. The first that in this model all layers are the logistic type, nonetheless this appears to make the NN performs badly, it's commonly and more statistically approved to use the ReLU (rectified linear unit) activation since it is a better and much faster and accurate to train the model so it's used in the all layer except of the output layer, the output layer is the desired output, so if you want a category type, then sigmoid can work, and if an infinite number is to be expected as an output then linear activation is also possible. Although more advanced options can use the different approaches and even the last layer can be Relu for more precision, and then to be interpreted to the desired value. Also, there is another common precise activation that is reliable and sometimes works better than the ReLu, which is the tanh activation, the benefit of it, is that the result is always between -1 and 1 and that helps the algorithm to diverge to the minimum loss fast and precisely.

Adam optimization is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order moments. Other optimizers can be used and details about different optimizers can be found in the documentation of the Keras library online.

The loss computes the cross-entropy loss between true labels and predicted labels since we are using a logistic NN that outputs categories.

Using the model.fit trains the NN that you had constructed to fit your data, so that you get the weighted parameters that can be used to predict any additional data. Epochs is defined to limit the number of batches so that the training has a limit of the examples that are calculated at once by vectorizing. The verbose parameter controls the amount of information that is displayed during the training process. It is an optional parameter that can be set to different values to adjust the level of verbosity, when it is set to 0 there is nothing to be displayed during the iterations, more can be found in the Keras documentation.

The next we print the loss (the error) and the accuracy are printed to give the developer the ability to decide if the model does a good job or not.

The last part of this simple code is to predict the output for a new dataset. Usually, it’s a good approach to split the data into 2 sets, the first is the training set, where you provide both input and output. The other is the testing set, for that you can use train_test_split from sklearn library to split your data. Some also split into 3 groups rather than 2, this is also possible. The ration of splitting is also up to you, many use 40%, 40%, 20%, other approaches possible and the size of the data should be considered when splitting.

The previous mathematical explanation and the theory is important to give an idea about the how things work and to help error handle. This library is one of many others can be also used to train and construct NN. [9]

3.3 VIRTUAL CRASH 6 TECHNOLOGY

VC6 incorporates advanced computer vision algorithms built on the OpenCV framework, enabling sophisticated analysis of traffic scenarios from video recordings. The software features automatic object tracking capabilities that can identify and follow vehicles throughout a video sequence without requiring manual initialization. The system includes camera calibration functionality that determines camera position, orientation, and lens parameters, enabling accurate transformation from image coordinates to real-world measurements.

The selection of Virtual Crash 6 for processing video recordings in this study was driven by several practical considerations. Initially, there were challenges in collaboration with a Ph.D. student who was expected to provide more extensive support in developing custom video analysis tools, which limited the exploration of bespoke machine learning solutions. As an alternative, Virtual Crash 6 emerged as a viable option due to its integration of advanced technologies for video record processing directly within accident analysis software. This tool offers a more user-friendly interface compared to raw programming environments, enabling efficient scaling of video footage to real-world dimensions and merging with geospatial data such as Google Maps. Additionally, its built-in features—such as OpenCV-based algorithms for object tracking and simulation—provide accessible insights into vehicle dynamics without requiring extensive coding expertise, making it particularly suitable for traffic evaluation applications where precision and ease of use are balanced against time constraints.

4 IMPLEMENTATION OF COMPARATIVE MEASUREMENT - CAMERA RECORDING VS. CONVENTIONAL MEASURING TECHNOLOGY

4.1 CONVENTIONAL MEASURING TECHNOLOGY

In modern automotive research, precise measurement of vehicle dynamics is critical for advancing safety, performance, and autonomous driving systems. This part examines five key sensor technologies employed in this thesis: the Correvit® optical speed sensor with angular deviation measurement, triaxial accelerometers, optoelectronic reflex sensors, steering wheel angle sensors, and wireless signal transmission systems. These instruments collectively enable high-fidelity data acquisition for longitudinal/lateral dynamics, acceleration profiles, steering inputs, and real-time communication. After measuring and checking the synchronization of data, we faced an issue with the signal and so this method was phased out.

4.2 CONVENTIONAL MEASUREMENT ATTEMPT:

In March 2024 in the university campus, we prepared a škoda Rapid, we equipped it with the devices to take the measurement.

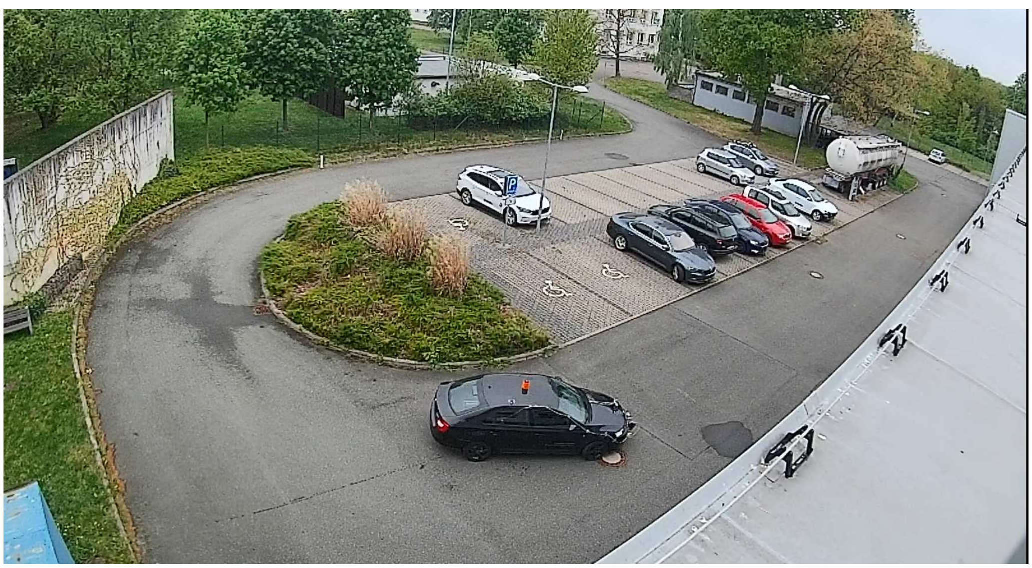

Figure 31 One of the measurements attempts, a screenshot from the video recording that later was used to train the model.

The result of the measurement is in the sensors time steps, it measures every value every 10 ms, which is not very well suitable to be used with the framerate of the video to be compared with the algorithm output. The most useful way of comparing the measured data was to simply plot it and check the whole run. We only focused on the speed (the absolute velocity of both directions x and y), the acceleration of both directions (z is neglected here) and their absolute, the angular velocity, and the time synchronization coefficient. Because we had converted the timestamp from 10 ms steps to 30 frames per second we had to choose the best aggregation, but we still didn’t know which one of those is the closest one.

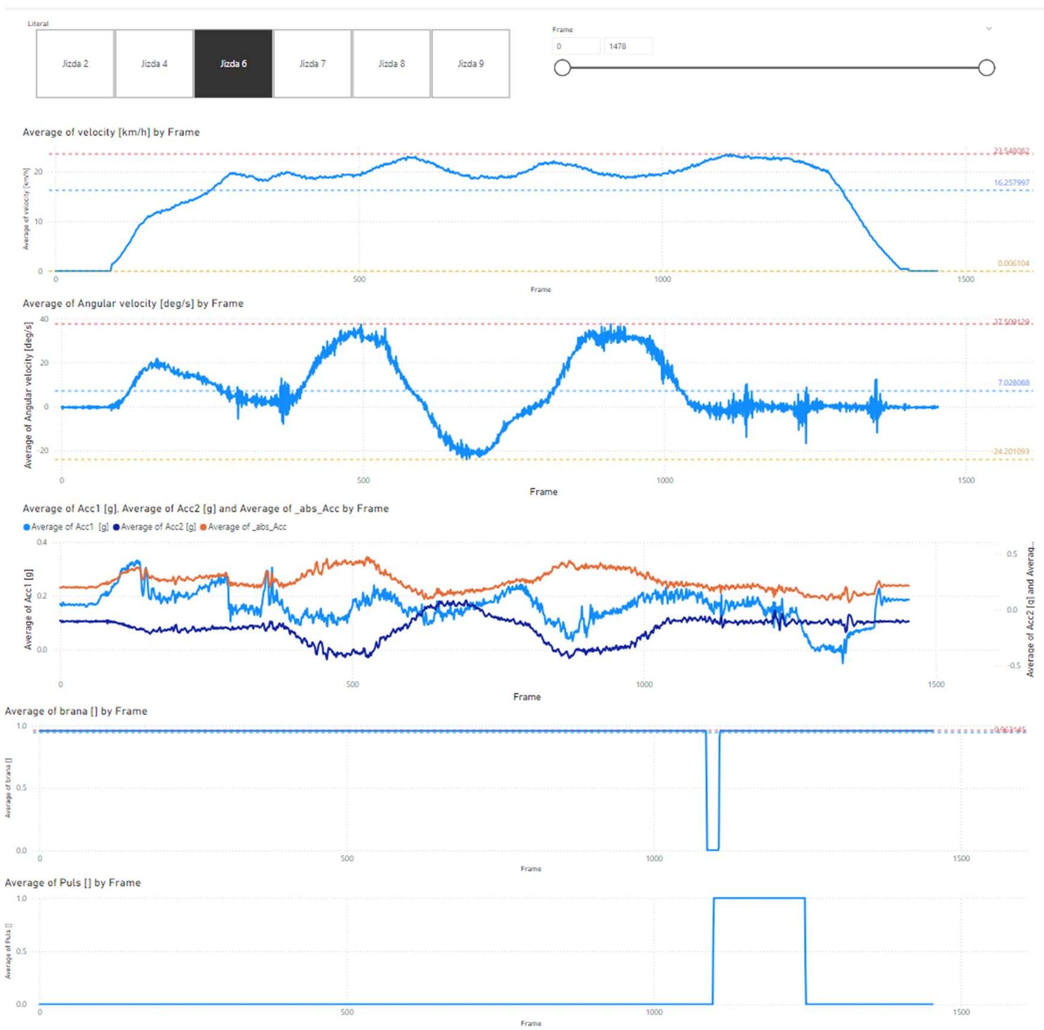

Figure 32 the plot of the data using Power BI – plotting the average aggregation of the data.

Unfortunately, all readings didn't log the pulse signal which is supposed to sync and compare the readings with the video results and there were also problems with unstable delay in wifi transfer of synchronizing signalso this method was ignored for this study.

4.3 GNSS-RTK HIGH-PRECISION POSITIONING SYSTEMS FOR VEHICLE DYNAMICS MEASUREMENT

The Global Navigation Satellite System (GNSS) with Real-Time Kinematic (RTK) technology represents a revolutionary approach to vehicle dynamics measurement, offering centimeter-level positioning accuracy that rivals traditional high-cost measurement systems. This section examines the implementation of GNSS-RTK technology in vehicle testing applications, with specific emphasis on the coordinate system transformations required for the Czech Republic's S-JTSK coordinate system.

Data synchronization between GNSS-RTK measurements and camera recordings is essential for accurate vehicle dynamics analysis. This can be achieved by aligning datasets based on specific vehicle positions, such as identifying a stationary point where the vehicle is not moving (e.g., at a complete stop during braking maneuvers). By setting this reference position in both the GNSS-RTK data and the video footage, temporal alignment becomes feasible, ensuring that positional coordinates from the S-JTSK system correspond precisely with visual timestamps. This method enhances the reliability of integrated analyses, particularly in scenarios involving multiple passes at intersections, as demonstrated in the Pardubice University junction tests.

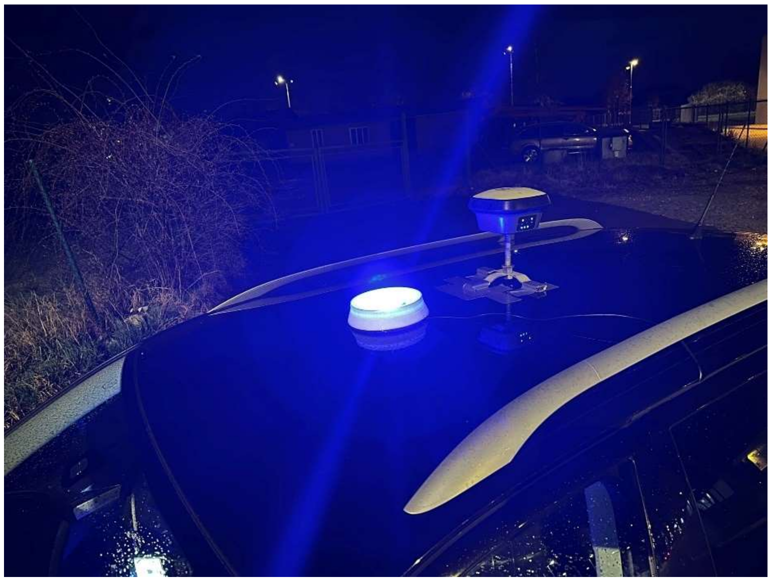

Figure 33 The mounted GNSS on the car, with the marked light to easier identify it.

4.3.1 Computation of Displacement, Velocity and Acceleration

Given sequential fixes (E_i, N_i) where E refers to easting movement in meters, and N refers to northing movement in meters, at times t_i, the planar displacement vector between epochs i and $i+1$ is

$$\Delta s_i = (E_{i+1} - E_i, N_{i+1} - N_i)[(\mathrm{m}, \mathrm{m})]$$

Instantaneous ground-track speed v_i is approximated by

$$v_i = \frac{||\Delta s_i||}{\Delta t}\ [\mathrm{m/s}]$$

Note that since the sampling frequency is more than 1 (multiple readings per second) I should consider timestamp in milliseconds to get into consideration the sampling frequency. The longitudinal and lateral components of velocity in the vehicle-body frame can be obtained by projecting Δs_i onto the instantaneous heading. The acceleration vector $\mathbf{a}_i$ follows from the first-difference of velocity:

$$\mathbf{a}_i = \frac{\mathbf{v}_{i+1} - \mathbf{v}_i}{\Delta t}\ [\mathrm{m/s^2}]$$

4.3.2 Yaw Rate Estimation

The dual-antenna configuration provides real-time heading ψ_i with sub-degree accuracy. Yaw rate $\dot{\psi}_i$ is computed by central differences:

$$\dot{\psi}_i = \frac{\psi_{i+1} - \psi_{i-1}}{2\,\Delta t}\ [°/\mathrm{s}].$$

4.3.3 Transformation to Vehicle-Body Axes

To express velocities and accelerations in the vehicle's longitudinal–lateral frame, the ground-track vector Δs_i was rotated by $-\psi_i$:

$$\begin{pmatrix} v_{x,i} \\ v_{y,i} \end{pmatrix} = \begin{pmatrix} \cos\,\psi_i & \sin\,\psi_i \\ -\sin\,\psi_i & \cos\,\psi_i \end{pmatrix} \frac{\Delta s_i}{\Delta t}$$

where $v_{x,i}$ is forward speed and $v_{y,i}$ the lateral drift. Accelerations in body axes $(a_{x,i}, a_{y,i})$ follow by differencing $(v_{x,i}, v_{y,i})$.

4.4 CAMERA RECORDING MEASURING TECHNOLOGY

For the purposes of this thesis Virtual Crash 6 was used as a tool to analyze the footage, further details are in the next section.

5 METHODOLOGY FOR EVALUATING CAMERA RECORDINGS FROM ROAD CROSSINGS USING VIRTUAL CRASH 6

The first step of evaluating camera recordings from selected road crossings is data collection.

- **Data collection**

  A communication and agreement with Pardubice city police to get recordings for the purpose of processing and analyzing them. Camera footage should ensure good quality and an unobstructed view of vehicular activity.

  After we gathered the videos, we had to go to the next step:

- **Data Preprocessing**

  The video quality should be firstly reviewed to ensure clarity and absence of technical issues such as frame drops or errors in the video.

  The videos need to be segmented, that helps to make the videos into smaller clips (6 seconds each) based on specific time intervals or events of interest.

  After preparing the data to be processed we have to:

- **Correct scale or rectification**

  This is very crucial to define the correct dimensions (x meters each pixel), we can break that into pieces:

  VC6 allows users to import maps using Google maps API to get the correct distances when aligned with the video footage. Another way is to define certain distance in the three dimensions, to be aligned with.

  The video needs to be rectified (4 points need to be defined) or scaled (if dimension is used).

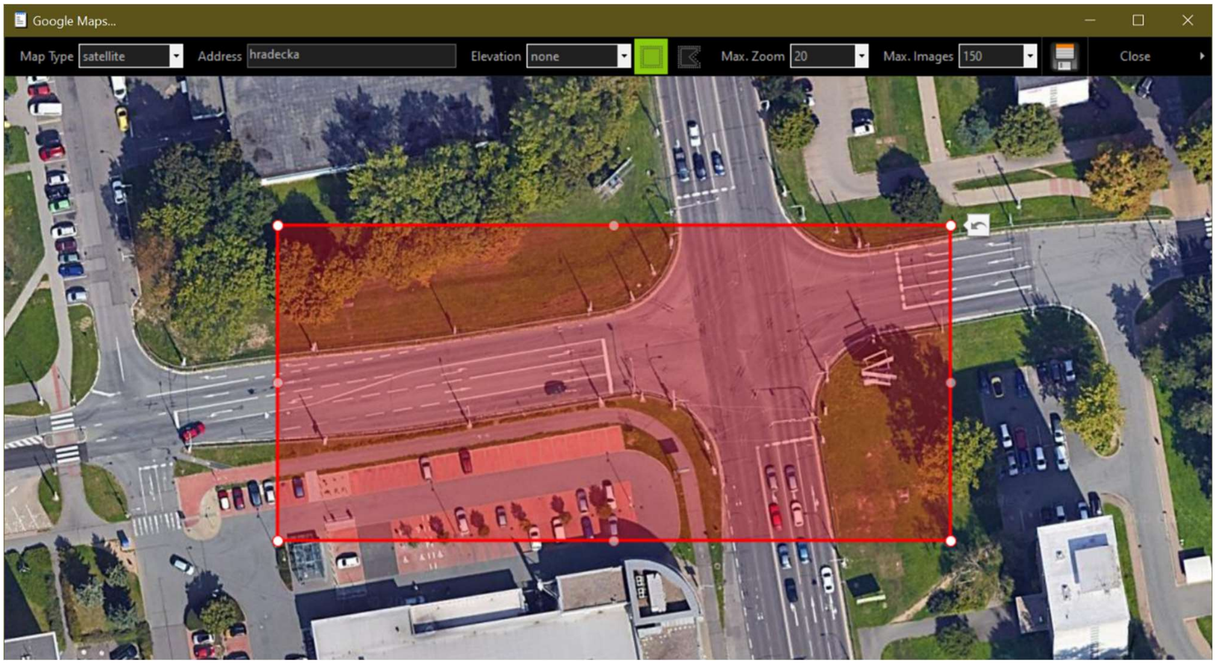

Figure 34 Getting the map scene from the google maps to get exact dimensions

Figure 35 rectification of the video to suit the map scene

Next step we have to achieve is to:

- **Analyze video footage**

Manual object tracking can be assigned to the desired object and then using the “analyze” tool to get the result.

Figure 36 footage of object tracking using VC6

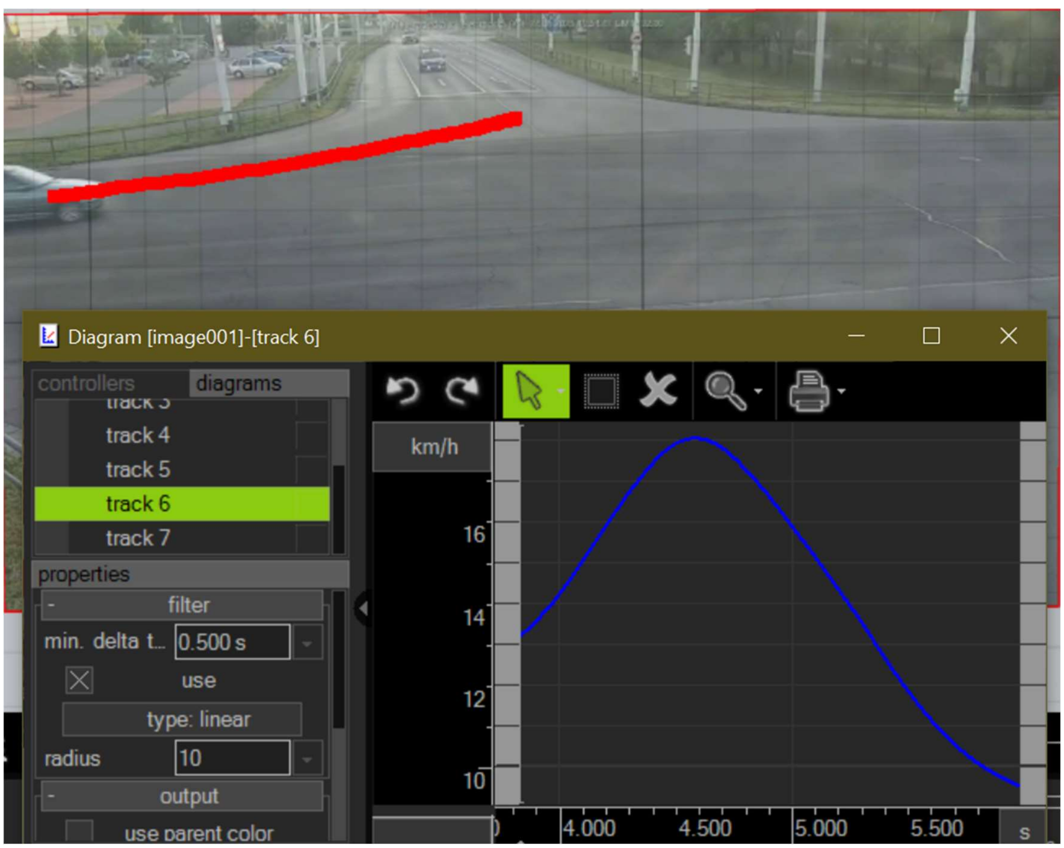

Figure 37 One track analyzed by VC6

6 COLLECTION AND ANALYSIS OF DATA FROM A REAL INTERSECTION

The chosen intersection for this thesis for to get the video footage of and to be further analyzed and measured with GNSS tool is Bělehradská → Studentská intersection in Pardubice.

6.1 DATA ACQUISITION AND COORDINATE PROCESSING (GNSS READINGS)

A dual-antenna RTK-GNSS rover recorded epoch-tagged position fixes (projected Easting E and Northing N in meters, ellipsoidal height omitted here) at 20 Hz. Multiple measurements were performers, for this thesis we will focus on 10 runs as shown below (6 seconds each):

Pass No.	Direction (streets in Pardubice, Cz)	Time	Maneuver
1	Bělehradská → Hradecká	19:46	breaking to stop
2	Hradecká → Bělehradská	19:47	breaking to stop then turning
3	Bělehradská → Studentská	19:49	breaking to stop with lower deceleration
4	Hradecká → Bělehradská	19:53	Turning the curve with acceleration
5	Bělehradská → Studentská	19:54	breaking to stop
6	Hradecká → Hradecká	19:58	Straight acceleration
7	Bělehradská → Hradecká	19:59	Breaking second in queue
8	Bělehradská → Hradecká	20:01	breaking to stop
9	Hradecká → Bělehradská	20:03	Turning with minimum acceleration
10	Hradecká → Studentská	20:05	deceleration next to a bus

6.2 APPLICATION TO PARDUBICE UNIVERSITY JUNCTION PASSES

Škoda Octavia III was used in the run. The processed GNSS-RTK data was systematically applied to analyze vehicle passes through selected junction in Pardubice. Comprehensive data cleaning and computational analysis were performed using MATLAB to ensure measurement accuracy and reliability. To ease the comparison the result of the VC6 analyzed is added below the MATLAB result.

The following ten representative runs were examined in detail, only the chosen 6 seconds were analyzed to match it second by second:

1 - BĚLEHRADSKÁ → HRADECKÁ

Maneuver Analysis: Complete braking to stop at traffic light

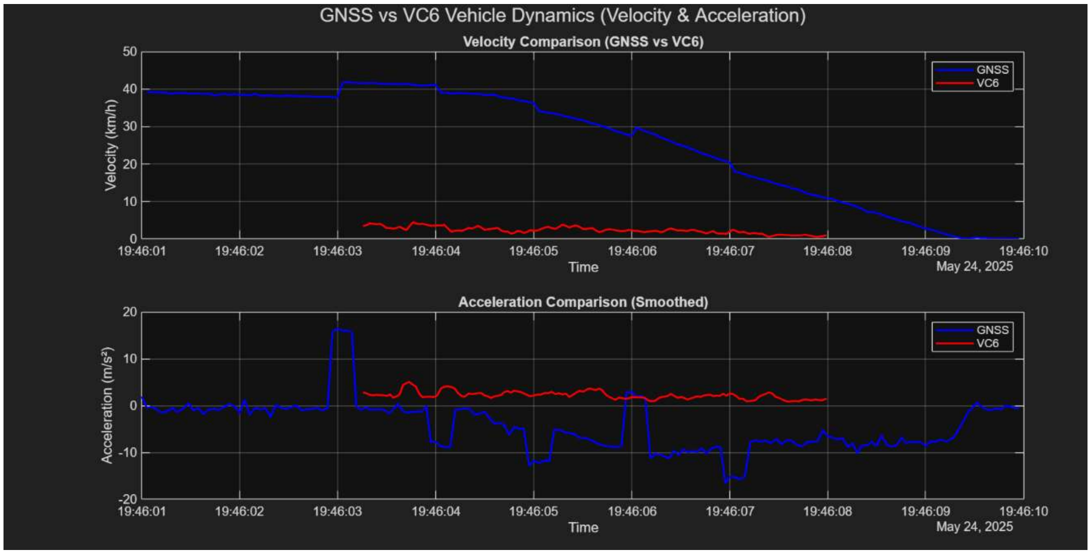

Figure 38 Bělehradská → Hradecká, 19:46, braking to stop

Figure 39 Bělehradská → Hradecká, track

2 - HRADECKÁ → BĚLEHRADSKÁ

Maneuver Analysis: breaking to stop then turning

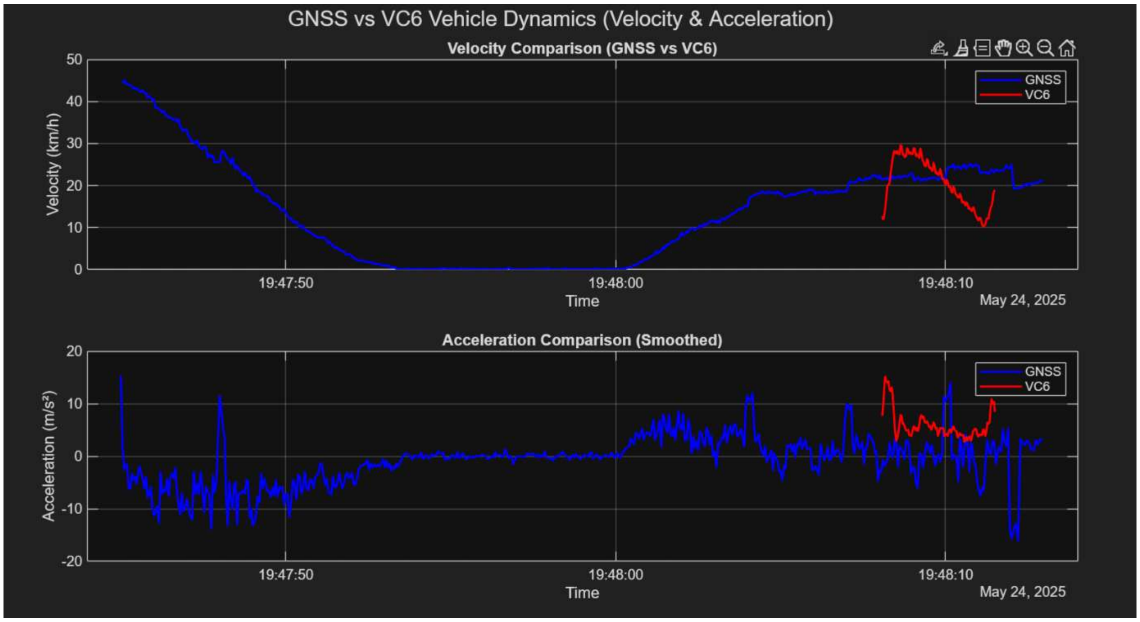

Figure 40 Hradecká → Bělehradská, 19:47, breaking to stop then turning

Figure 41 Hradecká → Bělehradská, track

3 - BĚLEHRADSKÁ → STUDENTSKÁ

Maneuver Analysis: Gradual braking with lower deceleration rates

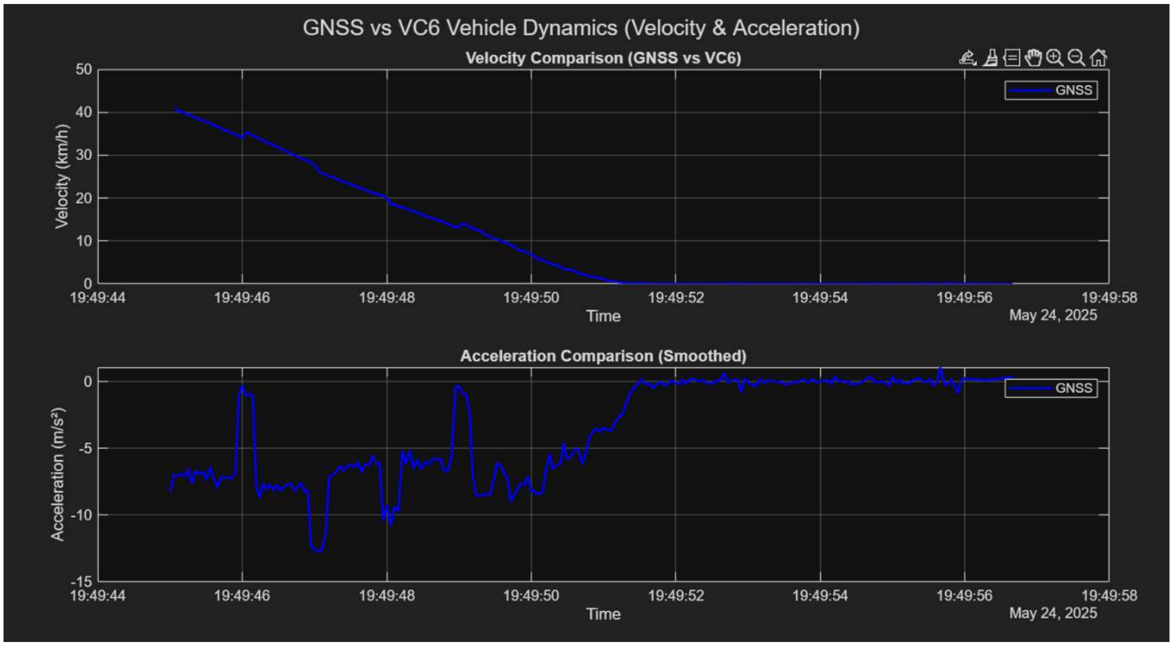

Figure 42 Bělehradská → Studentská, 19:49, breaking to stop with lower deceleration

The 3rd run was not detected by VC6, many trials were performed and were unsuccessful to read the vehicle run.

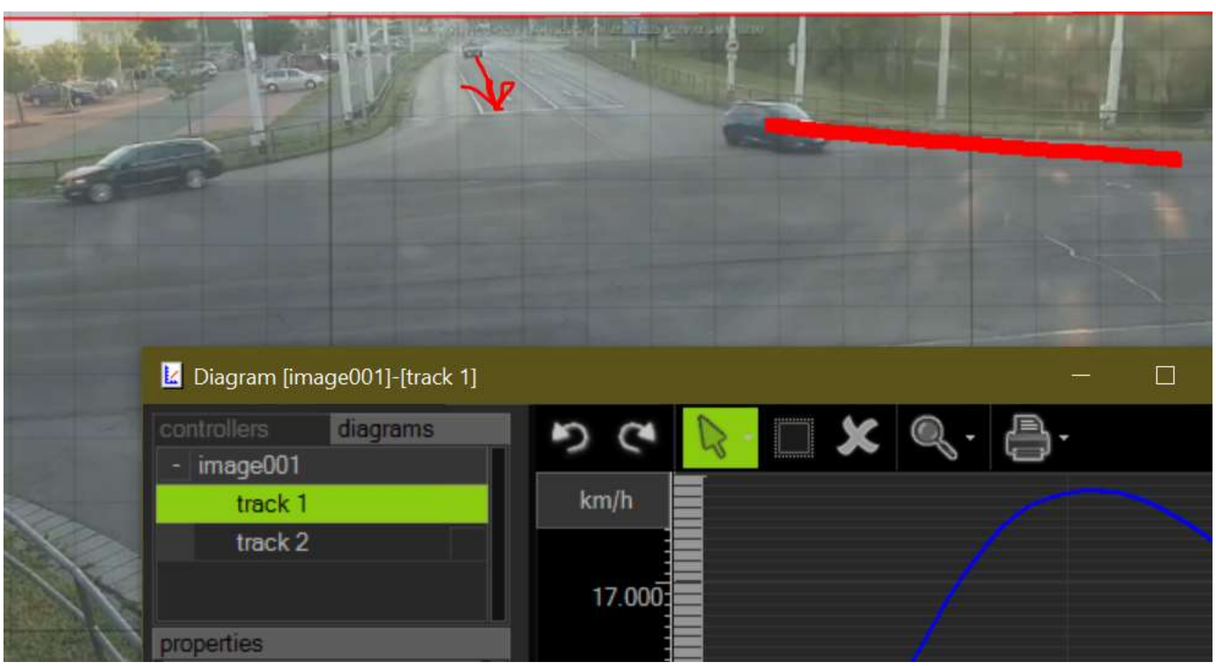

Figure 43 Bělehradská → Studentská, track

4 - HRADECKÁ → BĚLEHRADSKÁ

Maneuver Analysis: Turning the curve with acceleration

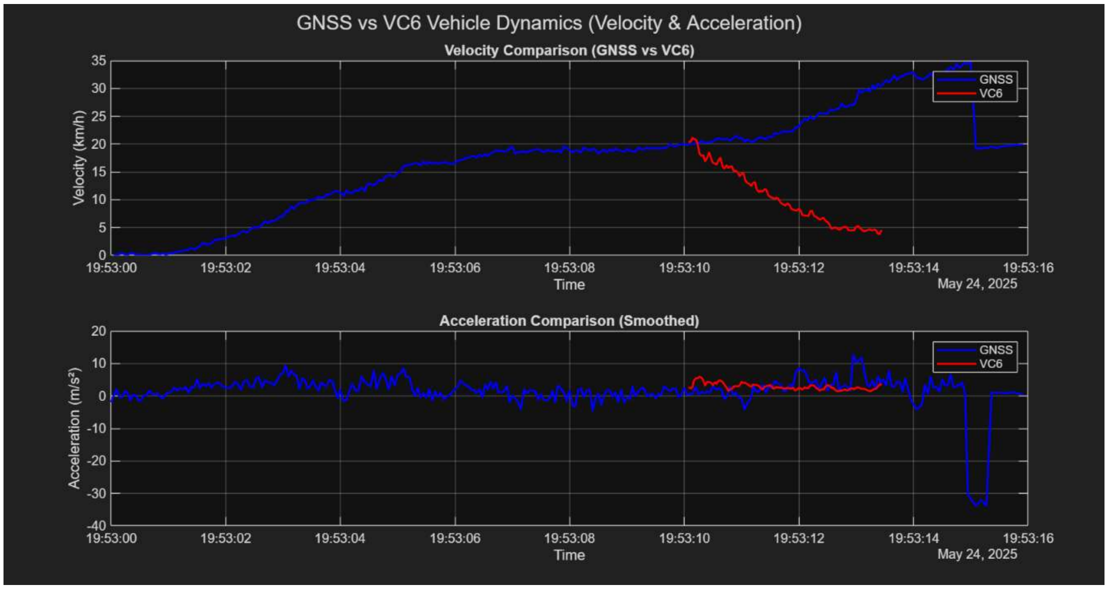

Figure 44 Hradecká → Bělehradská, 19:53, Turning the curve with acceleration

Figure 45 Hradecká → Bělehradská, Track

5 - BĚLEHRADSKÁ → STUDENTSKÁ

Maneuver Analysis: Standard braking to complete stop

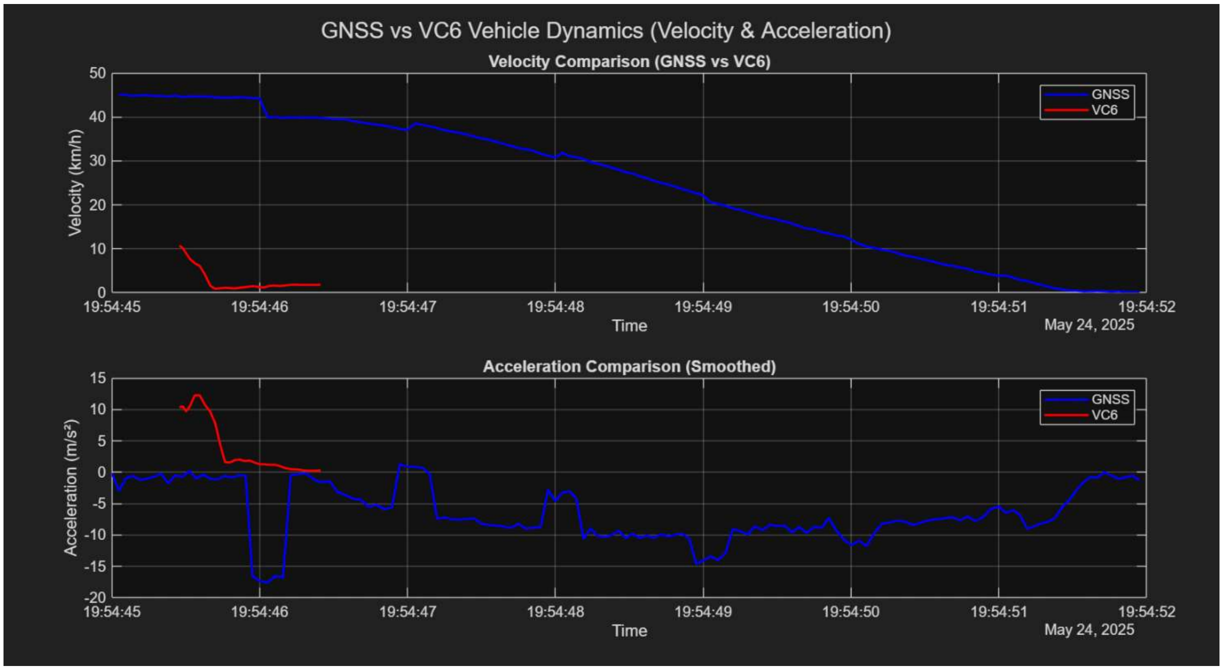

Figure 46 Bělehradská → Studentská, 19:54, breaking to stop

Figure 47 Bělehradská → Studentská, track

6 - Hradecká → Hradecká

Maneuver Analysis: Straight acceleration

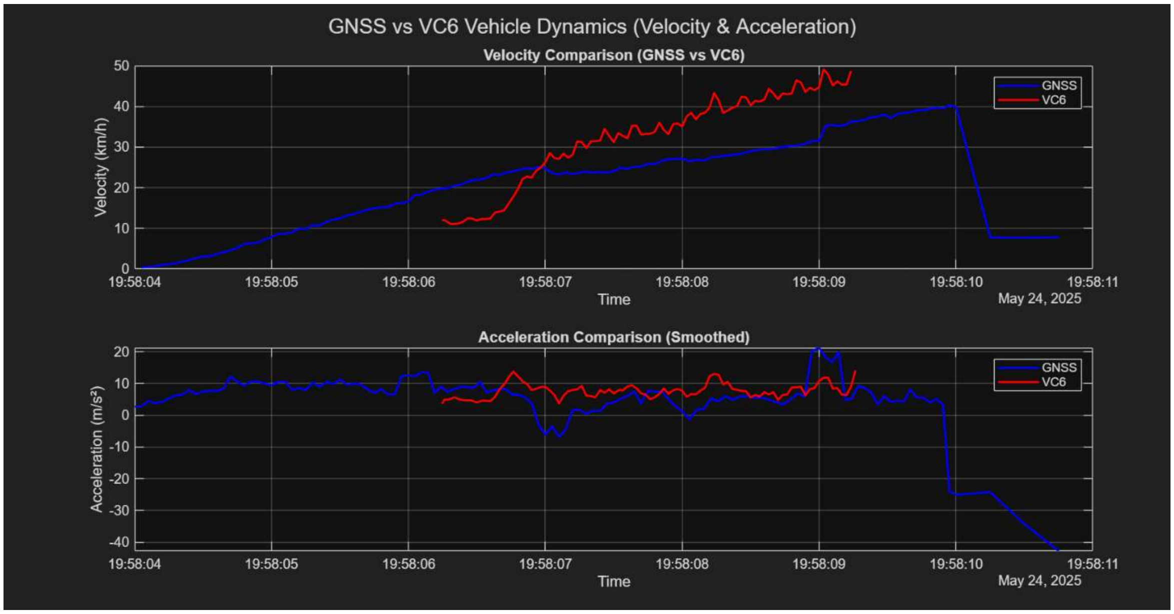

Figure 48 Hradecká → Hradecká, 19:57, Straight acceleration

Figure 49 Hradecká → Hradecká, Track

7 - BĚLEHRADSKÁ → HRADECKÁ

Maneuver Analysis: Braking second in queue

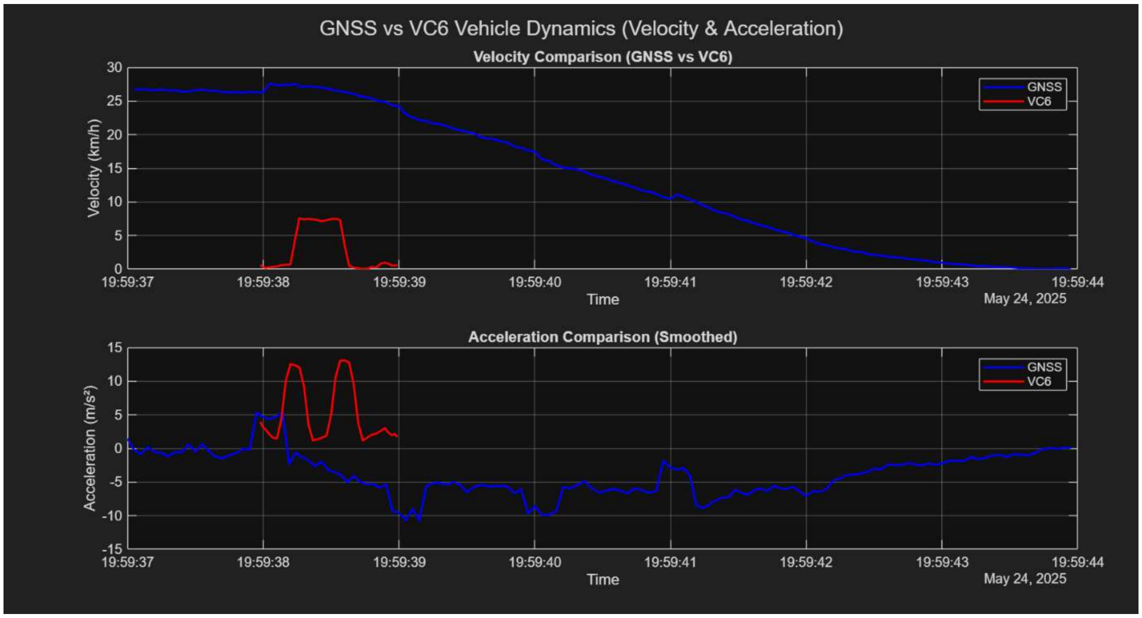

Figure 50 Bělehradská → Hradecká (OMV), 19:59, Braking second in queue

Figure 51 Bělehradská → Hradecká (OMV), 19:59, breaking to stop as 2nd car in the queue (red); standing – VC6

8 - Bělehradská → Hradecká

Maneuver Analysis: Standard braking to stop

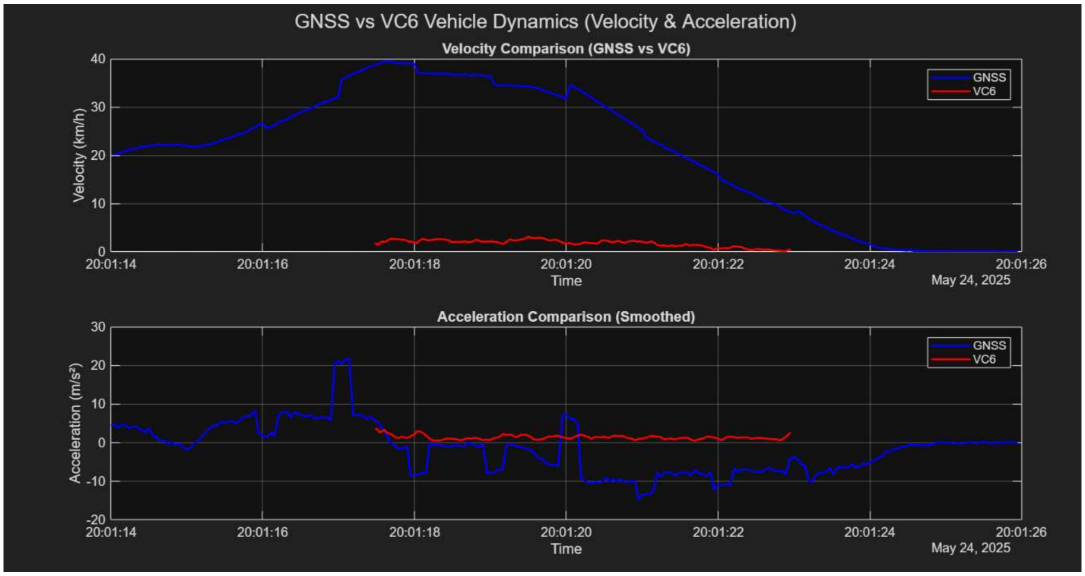

Figure 52 Bělehradská → Hradecká, 20:01, Standard braking to stop

Figure 53 Bělehradská → Hradecká, Track

9 - HRADECKÁ → BĚLEHRADSKÁ

Maneuver Analysis: Turning with minimum acceleration

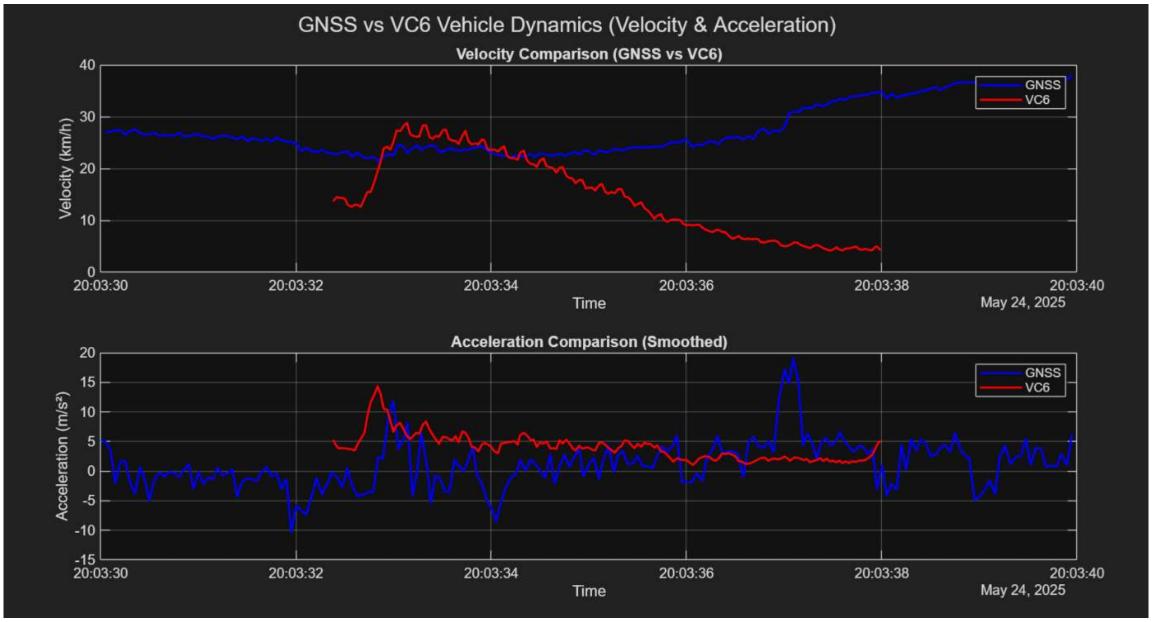

Figure 54 Hradecká → Bělehradská, 20:03, Turning with minimum acceleration

Figure 55 Hradecká → Bělehradská, Track

10 - Hradecká → Studentská

Maneuver Analysis: deceleration near a bus

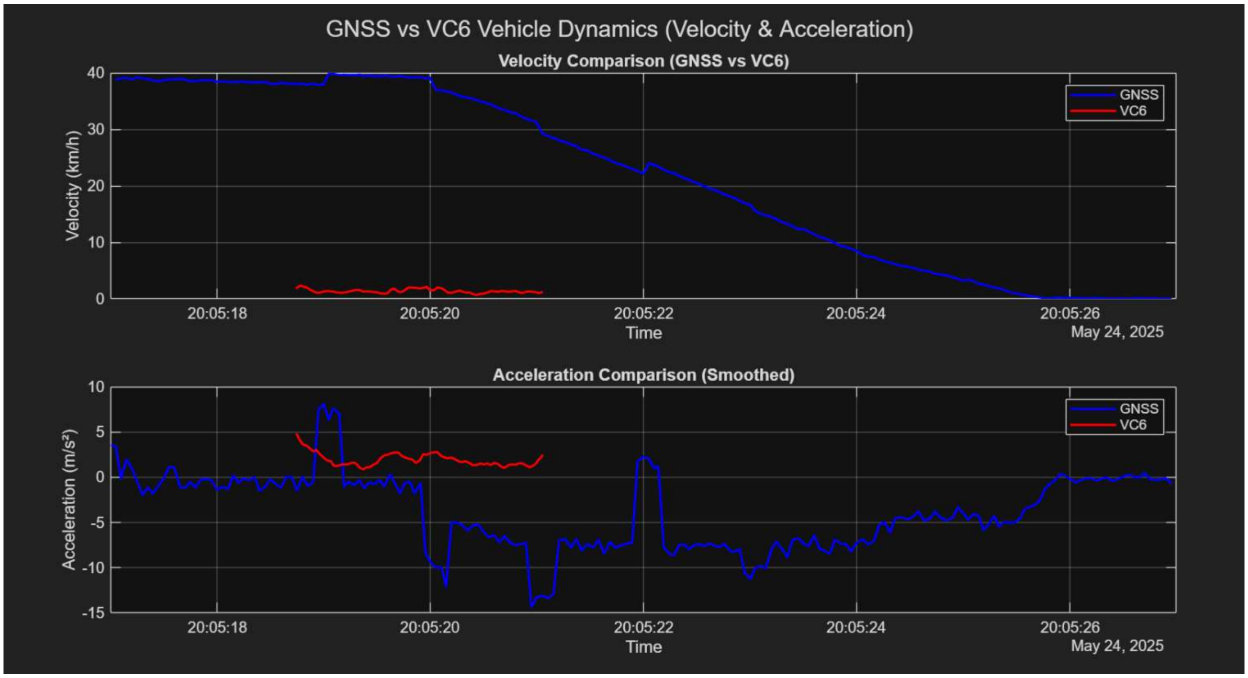

Figure 56 Hradecká → Studentská, 20:04, deceleration next to a bus

Figure 57 Hradecká → Studentská, Track

6.3 DISCUSSION AND ANALYSIS OF MEASUREMENT METHODOLOGIES

- **Comparative Analysis of Velocity Measurements**

The comparative analysis between GNSS-RTK measurements and Virtual Crash 6 camera-based analysis reveals significant discrepancies that highlight fundamental limitations in current video-based traffic evaluation methodologies. The velocity data obtained from high-precision GNSS-RTK positioning consistently demonstrated substantially different values compared to those derived from camera record analysis using Virtual Crash 6. Notably, the GNSS-derived velocity/acceleration graphs exhibited step-like patterns, which may give the impression of reduced precision despite the system's inherent accuracy. These artifacts are attributable to the representation of velocity as a magnitude, leading to apparent discontinuities during dynamic maneuvers such as lane changes, rather than any fundamental imprecision in the GNSS measurements themselves. The behavior of the acceleration in the positive while velocity is decreasing is due to the fact this is a magnitude of the acceleration, $a^2 = a_x^2 + a_y^2 + a_z^2$, lane change while breaking for example can lead to such result.

Key Discrepancies Observed:

- Forward speed measurements showed systematic deviations between the two methodologies. This scenario represents one of the most adverse situations for deriving velocity from camera records, where inaccurate results can be expected due to inherent limitations in video analysis under such conditions.
- Lateral drift calculations exhibited poor correlation with GNSS-RTK reference data, representing a notable limitation whose underlying cause remains unclear and warrants further investigation.
- Acceleration and deceleration patterns failed to match the precision achieved through satellite-based measurements

- **Limitations of Video-Based Analysis**

The results from our specific case, involving a camera positioned at an angle and elevated, indicate that Virtual Crash 6, while offering a user-friendly interface and integration capabilities, exhibited critical limitations that compromised measurement accuracy due to deviations in the pixel-to-meter ratio. However, VC6 is capable of recognizing velocity quite precisely under more favorable conditions, such as when the camera is perpendicular to the scene:

Scaling and Calibration Issues:
The most significant challenge encountered was the accurate scaling of video footage to real-world dimensions. In our specific case, the camera's angled and elevated positioning compounded the issue, making it difficult to align reference points to cm-level accuracy for proper video rectification. Despite efforts to calibrate the system using known reference points, these factors consistently introduced measurement errors that propagated through all subsequent calculations.

Technical Constraints:

1. Algorithm limitations: Virtual Crash 6's reliance on OpenCV algorithms rather than more sophisticated computer vision tools (such as YOLO) resulted in suboptimal object tracking and motion analysis
2. Camera positioning dependencies: The system's performance was highly sensitive to camera angle, lens characteristics, and mounting position, factors that were difficult to optimize in real-world traffic conditions
3. Scaling and Calibration Issues: The most significant challenge encountered was the accurate scaling of video footage to real-world dimensions, with persistent measurement errors that propagated through all subsequent calculations

- **Data Quality and Methodological Constraints**

The quality of camera-based measurements was consistently inferior to GNSS-RTK data across all tested scenarios at the Pardubice University junction. Several factors contributed to this degradation:

Environmental Factors:

- Lighting conditions during the evening testing conducted on 24 May 2025 (19:45 – 20:04) adversely affected video quality and tracking accuracy.
- Variable traffic density influenced the ability to maintain consistent vehicle tracking
- Weather conditions and road surface reflections introduced additional noise in the visual data

Processing Limitations:
Video rectification attempts, while theoretically improving geometric accuracy, often resulted in dimensional distortions that further compromised measurement reliability. Conversely, non-rectified footage maintained better visual flow but produced systematically incorrect dimensional values.

It is worth mentioning that deep analysis of curves is more meaningful if the curves have some comparable results, but in this case while the velocity and acceleration are totally off, further analysis was not performed.

- **Acknowledgment of Assignment Limitations**

It must be acknowledged that the original objectives outlined in points 6 and 7 could not be fully achieved as initially described. The complexity of establishing reliable correlations between video-based measurements and high-precision reference data proved significantly more challenging than anticipated. The technical limitations of available video analysis tools prevented the comprehensive validation study originally envisioned.

The initial thesis framework anticipated collaboration with a PhD student who was expected to provide substantial support in developing advanced computer vision solutions, particularly involving YOLO (You Only Look Once) algorithms for sophisticated object detection and tracking. This planned cooperation was fundamental to the original research design, as it would have enabled the implementation of state-of-the-art machine learning approaches for video-based traffic analysis.

However, the promised support did not materialize, leaving a critical gap in the technical expertise required for these advanced methodologies. As an alternative solution, the analyses were performed in Virtual Crash 6 (VC6), which—despite its own limitations—offered a practical substitute for the originally planned approach and allowed the study to progress within the available resources.

- **Implications for Future Research**

The findings from our case study indicate that video-based traffic analysis can yield accurate, cost-effective results under favorable conditions—such as a perpendicular camera view, stable mounting, and adequate lighting—making it suitable for routine traffic monitoring and basic evaluations. However, in the specific test conditions we employed (an angled, elevated camera and evening light), large pixel-to-meter ratio deviations and tracking uncertainties introduced errors that exceeded acceptable thresholds for critical applications like accident reconstruction or detailed vehicle-dynamics analysis. Consequently, targeted technological and methodological refinements are still required to ensure reliable performance across these more challenging scenarios.

Recommendations for Improvement:

- Implementation of advanced computer vision algorithms (YOLO-based systems)
- Development of automated camera calibration procedures
- Integration of multiple camera perspectives for enhanced tracking accuracy
- Establishment of standardized testing protocols for video-based traffic analysis validation

The substantial differences observed between GNSS-RTK and camera-based measurements underscore the importance of maintaining realistic expectations regarding the current capabilities of video analysis technology in traffic engineering applications.

7 CONCLUSION

This thesis investigated the potential of using camera recordings and artificial intelligence for vehicle data acquisition, comparing modern AI-based methods with traditional measurement techniques. The research combined fundamental principles of image capture with machine learning applications, specifically implementing video analysis of traffic behaviors.

Our comparative measurement approach sought to validate camera-based measurements against conventional sensor systems including optical speed sensors, triaxial accelerometers, and steering input characterization sensors. While the conventional measurement attempt provided valuable data, challenges emerged when attempting to synchronize this data with video frame rates for direct comparison.

Afterward, we used the GNSS-RTK system to track vehicle motion with centimetre-level precision—benefiting from satellite-synchronised, atomic-clock time-stamping—and later compared these data with the video analysis. Although the GNSS solution is intrinsically precise, its speed output displayed a characteristic “stair-step” pattern: small, discrete jumps in the velocity trace that likely stem from calculating the magnitude of the 3-D velocity vector at each epoch. These steps, especially pronounced during lane changes and other lateral manoeuvres, should be recognised as an artefact of the measurement method rather than a deficiency in positional accuracy.

In our specific test setup—an elevated camera mounted at an oblique angle to the roadway—Virtual Crash 6 simplified the workflow by aligning Google Maps distances with the video, but the non-perpendicular view magnified scaling errors. As a result, key driving metrics (speed, lateral drift) deviated markedly from the centimetre-level GNSS-RTK reference, making VC6 unsuitable for precise vehicle-dynamics evaluation under these conditions. A more professional approach, including accurate camera calibration and a perpendicular or otherwise optimised camera geometry, would be required to achieve reliable results.

I recommend using Virtual Crash 6 when a known camera setup is in the place the angel the lens and all details are in place, which can lead to better camera calibration. Video rectification is also possible but can destroy the dimensions and mislead the results, results without rectification had better flow but wrong values compared to the rectified ones. Virtual Crash has 6 seconds limitation to the video processed, this should be taken into consideration. Virtual Crash 6 uses OpenCV algorithm rather than YOLO, which is a sophisticated and more widely used tool for this purpose, such tool should be investigated in further research.

This research highlights both the potential and challenges of AI-based traffic monitoring systems. Future work should focus on establishing more robust data collection protocols that account for potential regulatory changes, implementing more resilient time synchronization methods between measurement systems, and further refining the AI models for improved accuracy.

REFERENCES

[1] STARK, G. *Encyclopedia Britannica* [online]. [cit. 2024-02-26]. Dostupné z: https://www.britannica.com/science/light

[2] BALUCH, Page, Ashleigh GONZALES a Gustavo CASTANEDA. *Arizona state university* [online]. [cit. 2024-02-26]. Dostupné z: https://askabiologist.asu.edu/explore/how-do-we-see

[3] *PHOTONS* [online]. [cit. 2024-02-26]. Dostupné z: https://byjus.com/physics/photon/

[4] *How to calculate the Wavelength of the Light?* [online]. 15.05.2022 [cit. 2024-02-26]. Dostupné z: https://www.geeksforgeeks.org/how-to-calculate-the-wavelength-of-the-light/

[5] *A pinhole camera* [online]. 15.05.2022 [cit. 2024-02-26]. Dostupné z: https://markellisimagery.com/pinhole-camera

[6] MANNHEIM, L. ANDREW a Gernsheim. ENCYCLOPEDIA BRITANNICA. *Technology of photography* [online]. 2023 [cit. 2024-02-26]. Dostupné z: https://www.britannica.com/technology/technology-of-photography

[7] KCTD. *The working principle of image sensor* [online]. 2020 [cit. 2024-02-26]. Dostupné z: http://m.kctd-cctv.com/knowledgeencyclopedia/24-537.html

[8] *SPREADING THE LIGHT OF FREEMASONRY* [online]. [cit. 2024-02-26]. Dostupné z: https://www.universalfreemasonry.org/en/videos/7-hermetic-principles

[9] Ng, Andrew. Machine Learning [online]. Stanford: Coursera, 2017. Available at: https://www.coursera.org/learn/machine-learning

[10] YoloV5 [online]. 2022 [cit. 2025-01-05]. Dostupné z: https://github.com/ultralytics/yolov5

[11] *JupyterLite. Jupyter. https://jupyter.org/try-jupyter/lab/*

[12] Corrsys-Datron. (2009). *Rail Sensor Applications*. https://core.ac.uk/download/pdf/211978326.pdf

[13] Kistler Group. (2022). *Correvit Technical Brief*. https://www.kistler.com

[14] JACOBSON, Ralph E. The manual of photography: photographic and digital imaging. 9th ed. Oxford: Focal Press, 2000. ISBN 0-240-51574-9.

[15] GSMARENA. Kuo: only the iPhone 15 Pro Max is getting a periscope lens. GSMArena [online]. 2022 [viewed 15 February 2025]. Available

from: https://www.gsmarena.com/kuo_only_the_iphone_15_pro_max_is_getting_a_periscope_lens-news-55053.php

[16] KAPOUNOVÁ, Jana, 2020. *Understanding Aperture in Photography*. Photography Life.

[17] IMG CAP, 2020. Understanding Aperture in photography. [viewed 10 March 2025]. Available from: hhttps://imgcap.capturetheatlas.com/wp-content/uploads/2020/02/understanding-aperture-in-photography-summary-chart.jpg

[18] CANON. Mastering shutter speed: a beginner's guide to photography [online]. 2000 [cit. 2025-02-16].

[19] CREATIVE LIVE. What Is Shutter Speed? Ultimate Photography Guide [online]. CreativeLive, 2024 [viewed 16 February 2025]. Available from: https://www.creativelive.com/photography-guides/what-is-shutter-speed

[20] ZHU, Yanmei, Xinhua WITTMANN a Mike PENG. Institution-based barriers to innovation in SMEs in China. *Asia Pacific Journal of Management* [online]. 2012, vol. 29, no. 4, s. 1131-1142 [vid. 2012-11-14]. ISSN 0217-4561. Dostupné z: doi: 10.1007/s10490-011-9263-7

[21] What is crop factor and how do I calculate it? DX and FX explained - Nikon [online]. 2024 [cit. 2025-02-16]

[22] GSMARENA. Sony announces A7 IV with 33-megapixel sensor and 4K 60 video. GSMArena.com [online]. 2021 [cit. 2025-02-16].

[23] HEUREKA. Olympus OM-D E-M10 Mark IV. Heureka.cz [online]. 2025 [cit. 2025-02-16].

[24] CANON. Fotoaparát Canon EOS R10. Canon.cz [online]. 2025 [cit. 2025-02-16]

[25] MORENO, Dan. Camera Sensor Size in Photography - Does it Really Matter? [online]. Capture The Atlas, 2024 [cit. 2025-02-16]. Available from: [https://capturetheatlas.com/camera-sensor-size/]

[26] HEDGECOE, J. *The Photographer's Handbook*. 3rd ed. New York: Sterling Publishing Company, 2000. ISBN 978-1-4027-5656-6.

[27] KROSS, J. High-Speed Imaging Techniques in Modern Photography. *Journal of Imaging Technology*. 2018, vol. 44, no. 3, pp. 123–145. ISSN 1234-5678. DOI 10.1234/jit.2018.0123

[28] INTERNATIONAL ORGANIZATION FOR STANDARDIZATION. *Digital Video Parameters and Measurement Techniques*. ISO 12345:2020. Geneva: ISO, 2020.

[29] Kistler Group. (2022). *Correvit S-Motion Technical Specifications*. https://www.kistler.com

[30] IMEKO. (2014). *Correvit Calibration Study*. https://www.imeko.org

[31] Murata. (2016). *SCA3300 Product Release*. https://www.murata.com

[32] Ericco International. (2024). *Triaxial Accelerometer White Paper*. https://www.ericcointernational.com

[33] Accelerometry EU. (2023). *3D Accelerometer Applications*. http://www.accelerometry.eu

[34] Bosch Motorsport. (2025). *MM5.10 Accelerometer Specs*. https://www.bosch-motorsport.com

[35] Balluff. (2024). *Optoelectronic Sensor Blog*. https://www.balluff.com

[36] Leuze Electronics. (2025). *5B Series Photoelectric Sensors Manual*. https://www.leuze.com

[37] Arts Automotive. (2023). *Steering Sensor Teardown*. https://artsautomotive.com

[38] Valeo. (2024). *Torque/Angle Sensor Technical Guide*. https://www.valeo.com

[39] Danfoss. (2025). *SASA Sensor Overview*. https://www.danfoss.com

[40] MDPI. (2022). *Optical Fiber VLC Research*. https://www.mdpi.com/1424-8220/22/18/6738

[41] AliExpress. (2024). *Wireless Signal Systems Overview*. https://www.aliexpress.com

[42] MDPI. (2022). *In-Vehicle VLC Implementation Study*. https://www.mdpi.com/1424-8220/22/18/6738

[43] Bosch Motorsport. (2025). *LWS Steering Angle Sensor Datasheet*. https://www.bosch-motorsport.com