



Neural-Assisted Feature Matching

Internship Report

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Chapter 2

Introduction

2.1 Host Organism

2.1.1 SteelSeries

Company history and Background

SteelSeries, a danish manufacturer of gaming peripherals, was founded in 2001 by Jacob Wolff-Petersen. The company originally launched under the name Soft Trading, and made its mark with innovative gaming mousepads in the early 2000s. In 2007, Soft Trading rebranded to SteelSeries, reflecting its broadened focus beyond mousepads and into a full range of PC gaming accessories. Key milestones in SteelSeries' evolution include the acquisition of Ideazon in 2008, which brought the Zboard and World of Warcraft gaming keyboard into its portfolio, and further its presence in the North American market. The company grew rapidly in the 2010s, fueled by its involvement in the esports scene and partnerships with professional gamers. SteelSeries has since expanded its product line to include high-performance gaming mice, keyboards, headsets, and mousepads, becoming a leading brand in the gaming industry.

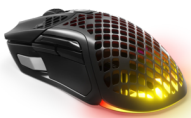
Key Products and Technologies

SteelSeries, renowned for its gaming peripherals and accessories, spanning several product categories. Its product portfolio includes:

- **Gaming Mice:** High-precision mice with customizable buttons and sensors.



(a) Rival 3 Wireless Gen
2



(b) Aerox 5



(c) Rival 5

Figure 2.1: SteelSeries Gaming Mice

- **Keyboards:** Mechanical and membrane keyboards designed for gaming performance.



(a) Apex Pro Gen 3



(b) Apex Pro Mini Gen 3



(c) Apex Pro TKL Gen 3

Figure 2.2: SteelSeries Gaming Keyboards

- **Headsets:** Wired and wireless headsets with advanced audio features.



(a) Arctis Nova 3 Wireless



(b) Arctis Pro Wireless



(c) Arctis GameBuds™ Glorange

Figure 2.3: SteelSeries Gaming Keyboards

- **Mousepads:** Various sizes and materials optimized for different play styles.
- **Software:**
 - **SteelSeries GG:** the all-in-one software platform that brings together the various tools and services SteelSeries offers to enhance the gaming experience. It serves as the central hub for managing SteelSeries peripherals and includes multiple sub-applications.
 - **SteelSeries Engine:** the part of GG that handles the core device configuration. It's used to customize settings for SteelSeries mice, keyboards, headsets, and other gear. Through Engine, users can adjust RGB lighting effects, set up macros, fine-tune mouse sensitivity (DPI).
 - SteelSeries' advanced audio suite built specifically for gamers who want precise control over their sound experience. It offers a powerful parametric equalizer that lets users independently customize audio for game sounds, voice chat, and microphone input.
 - **SteelSeries Moments:** a gameplay capture tool within GG that automatically records key moments during gaming sessions. It can detect in-game events like kills, wins, or goals and save short clips around those events.

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2.1.2 Mission

SteelSeries' mission is to create the best gaming gear in the world, empowering gamers to perform at their best, whether it is for professional who seek perfection, or casuals who seek a sense of competition and completion. It's implication over the years in the esports scene has made it a trusted brand among professional gamers, and its commitment to innovation continues to drive the development of new products that enhance the gaming experience. Most notably, SKT Gaming, a professional esports organization, has been using SteelSeries products since 2012, and has won multiple championships in games like CS:GO and League of Legends etc.



Figure 2.4

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