

TITLE

Thesis submitted in partial fulfillment
of the requirements for the degree of

Master of Science
in
Programme
by Research

by

NAME

ROLL NUMBER

EMAIL ID



International Institute of Information Technology

(Deemed to be University)

Hyderabad - 500 032, INDIA

MONTH YEAR

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International Institute of Information Technology
Hyderabad, India

CERTIFICATE

It is certified that the work contained in this thesis, titled “**TITLE**” by **NAME**, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date

Adviser: Prof. NAME

To SOMEONE

Acknowledgements

Acknowledgements goes here ...

Abstract

Abstract goes here ...

Contents

1	Introduction	1
1.1	Robotic Systems	1
1.1.1	General Autonomous Agents	1
1.1.2	Localization and Mapping	1
1.1.3	Visual Place Recognition	1
1.2	Foundation Models	1
1.3	Contribution	1
2	Foundation Models	2
2.1	Vision Transformers	2
2.2	SSL Concepts	2
2.3	DINO and DINOv2 details	2
3	AnyLoc: Foundation model features for VPR	3
4	Future Scope	4
5	Conclusions	5
	Bibliography	7

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Robotic Systems

Write in the end. Add the following in this section

- Components of an autonomous robot system: Environment + Perception + Localization and map building + Cognition, path planning + Motion control. Highlight Localization and map building (as "contributed area").
- Parts of a localization (SLAM) system and where VPR plays a role
- Image retrieval as a part of VPR systems. Elaborate the space/place of VPR (very brief of [8]).

1.1.1 General Autonomous Agents

A brief on AGI for autonomous robots. Open set works with Foundation Models (that work in any setting) are trending: Drive Anywhere [23], MUVO [2], GAIA [14].

1.1.2 Localization and Mapping

Info on SLAM systems

1.1.3 Visual Place Recognition

VPR and image retrieval

1.2 Foundation Models

Brief on Foundation Models. Two paragraphs maximum.

1.3 Contribution

List the contributions of the work in this thesis

Chapter 2

Foundation Models

All the basics of Vision Foundation Models required for understanding this thesis.

Foundation models (virtually all AI modes in general) have the following components

- *Model architecture*: MLP, convolution, transformers. Also MLP mixer [21], ConvNext [18], transformer variants (CCT) [10], etc.
- *Dataset*: type (labelled for supervised, unlabelled for unsupervised or self-supervised), size (large), augmentations, data processing pipelines.
- *Objective, training strategy and Loss function*: formulation of training procedure to guide the model output. Distillation [13], representation learning, MAE [11], contrastive losses (aligning modalities), knowledge transfer (student-teacher), MoCo [12, 6], SwAV [3], SimCLR [4, 5], BYOL [9], etc.
- *Optimizer*: usually Adam [17] (doesn't need explanation)

2.1 Vision Transformers

ViT [7] and DeiT [22]

2.2 SSL Concepts

Start with a short summary of the SSL cookbook [1].

Some of the above along with requirements for DINOv2: iBOT [24], LayerScale and Stochastic Depth [15], KoLeo regularizer [19], SwiGLU activation [20], Sinkhorn-Knoop centering [3] (SwAV).

2.3 DINO and DINOv2 details

Architecture, data, training, etc.

Chapter 3

AnyLoc: Foundation model features for VPR

Description of AnyLoc [16]

Chapter 4

Future Scope

What else can be done ahead for AnyLoc.

- Results with PCA seem promising, more model optimizations could give better results (with higher throughput/faster speed)
- Integration into a full SLAM system

Chapter 5

Conclusions

Something

Related Publications

1. Keetha, N.V., *Mishra, A.*, Karhade, J., Jatavallabhula, K., Scherer, S.A., Krishna, M., & Garg, S. (2023). AnyLoc: Towards Universal Visual Place Recognition. *IEEE Robotics and Automation Letters*, 9, 1286-1293. doi: 10.1109/LRA.2023.3343602 (arXiv: 2308.00688)

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