Vision-Language-Action Models for Embodied AI

A Deep Dive into the 2024 Survey

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What is Embodied AI?

- AI that lives in the real world, not just on a screen
- Can see, understand, and take actions
- Example: A robot that follows the command “bring me a cup”
- It combines vision, language, and movement
- Not like ChatGPT or CLIP – they don’t interact with the physical world

Why Do We Need VLA Models?

- Real-world tasks are complex and multi-step
- Robots must understand what to do, what they see, and how to act
- One model for just vision or just language is not enough
- VLA models let robots follow natural commands like humans
- Helps in homes, hospitals, factories, and more

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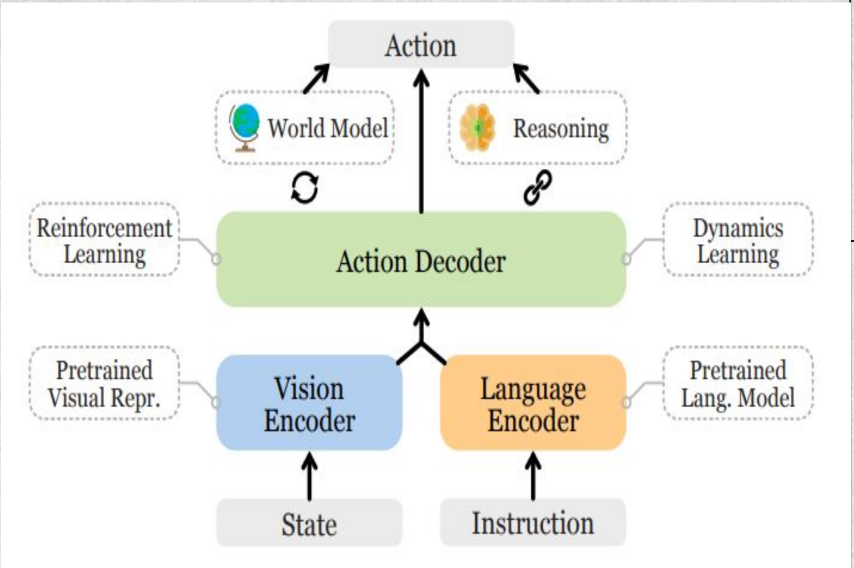
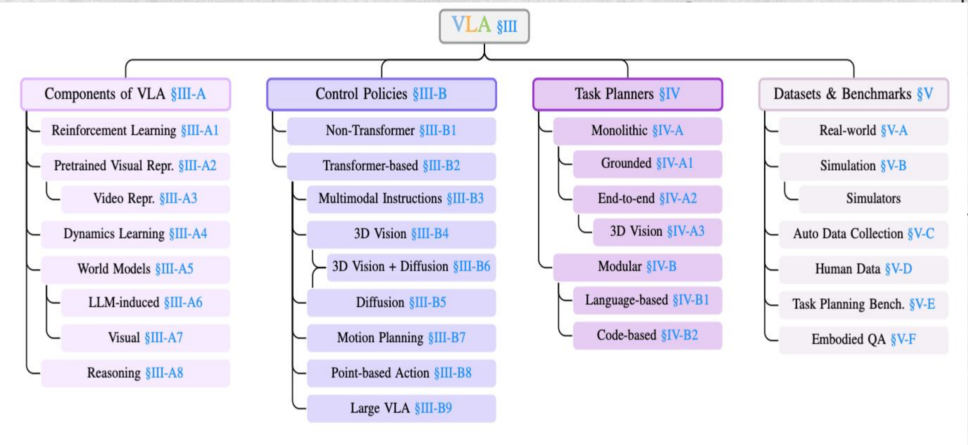


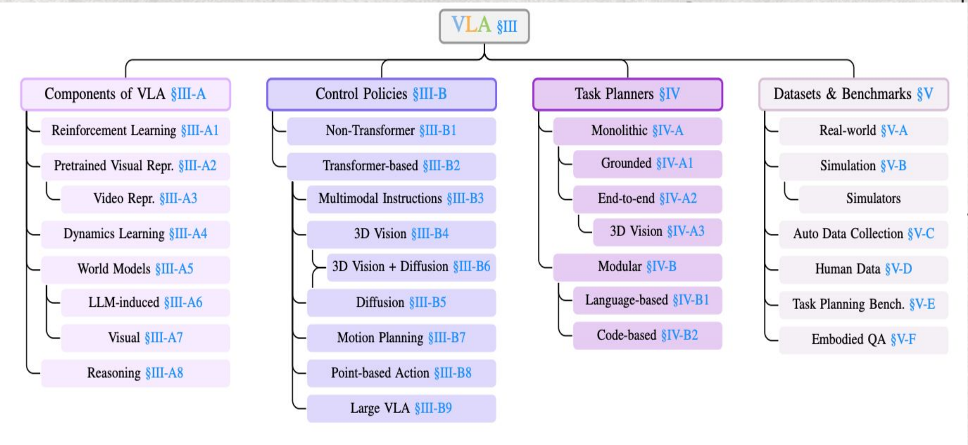
The Three Main Parts of VLA Models

- VLA models have 3 main parts:
    1. **Components** – visual/language encoders and world models
    2. **Low-Level Control** – small step actions (e.g. move, pick)
    3. **High-Level Planners** – break big tasks into small steps
- This structure helps models plan and act better
- Like a team: planner = brain, controller = hands



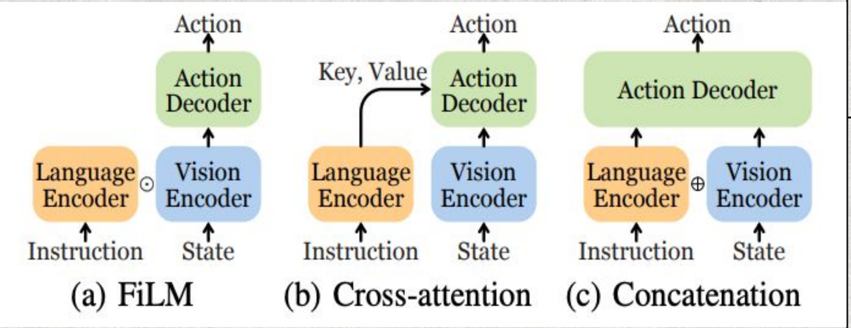
Key Components

- Vision Encoder – helps robot "see" (e.g. CLIP, R3M, MVP)
- Language Encoder – understands commands (e.g. BERT, GPT)
- Dynamics Model – learns how actions change the world
- World Model – predicts what will happen next (like a mini-simulator)
- These parts work together to help the robot think before it moves



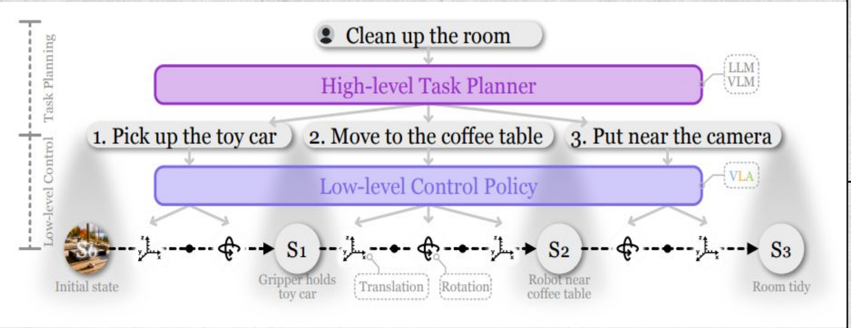
Low-Level Control

- Low-level control = small actions like pick, move, turn
- Uses info from camera + instruction to act in real-time
- Common methods:
  - FiLM – adjusts vision using language
  - Cross-Attention – connects vision + language deeply
  - Concatenation – joins both inputs together
- Models: CLIPort, BC-Z, RT-1, UniPi
- Some use transformers or even learn from videos



High-Level Task Planners

- Planner breaks long tasks into smaller actions
- (e.g. “clean room” → pick up toy → wipe table)
- Two common types:
    - Language-based: LLM writes out steps in text
    - Code-based: LLM creates commands using functions like pick() or move()
- Helps robot know what to do next
- Famous examples: SayCan, InnerMonologue, ProgPrompt



Training Data and Benchmarks

- Real robot data is hard to collect and expensive
- Simulators are used for faster and safer training (e.g. Habitat, AI2-THOR)
- Some models learn from human videos or internet data
- Benchmarks help test models:
  - EmbodiedQA: ask + explore
  - RLBench: robot manipulation
  - EgoPlan / PlanBench: test planning skills
- Important to compare models fairly

Name	Scenes /Rooms	Objects /Cat	UI	Physics Engine	Task	Observation	Action	Agent	Description	Related
Gibson [190]	572/-	-	-	Pybullet	Navi	RGB, D, N, S	-	-	Navi only	-
iGibson [189], [191], [192]	15/108	152/5	Mouse, VR	Pybullet	Navi, Mani	RGB, D, S, N, Flow, LiDAR	Force	TurtleBot v2, LoCoBot, etc.	VR, Continuous Extended States. Versions: iGibson 0.5, 1.0, 2.0	Benchmarks: BEHAVIOR-100 [188], BEHAVIOR-1K [193]
SAPIEN [194]	-	2346/-	Code	PhysX	Navi, Mani	RGB, D, S	Force	Franka	Articulation, Ray Tracing	VoxPoser. Benchmarks: SIMPLER [195]
AI2-THOR [196]	-/120	118/118	Mouse	Unity	Navi, Mani	RGB, D, S, A	Force, PD	ManipulaTHOR, LoCoBot, etc.	Object States, Task Planning. Versions: [197], [198]	Benchmarks: ALFRED, RoPOR [199]
VirtualHome [200]	7/-	-/509	Lang	Unity	Navi, Mani	RGB, D, S	Force, PD	Human	Object States, Task Planning	LID, Translated⟨LM⟩, ProgPrompt
TDW [201]	15/120	112/50	VR	Unity, Flex	Navi, Mani	RGB, D, S, A	Force	Fetch, Sawyer, Baxter	Audio, Fluids	-
RLBench [102]	1/-	28/28	Code	Bullet	Mani	RGB, D, S	Force	Franka	Tiered Task Difficulty	Hiveformer, PerAct
Meta-World [202]	1/-	80/7	Code	MuJoCo	Mani	Pose	Force	Sawyer	Meta-RL	R3M, VC-1, Vi-PRoM, EmbodiedGPT
CALVIN [203]	4/-	7/5	-	Pybullet	Mani	RGB, D	Force	Franka	Long-horizon Lang-cond tasks	GR-1, HULC, RoboFlamingo
Franka Kitchen [204]	1/-	10/6	VR	MuJoCo	Mani	Pose	Force	Franka	Extended by R3M with RGB	R3M, Voltron, Vi-PRoM, Diffusion Policy, EmbodiedGPT
Habitat [205], [206]	Matterport + Gibson		Mouse	Bullet	Navi	RGB, D, S, A	Force	Fetch, Franka, AlienGO	Fast, Navi only. Versions: Rearrangement [207], Habitat 2.0	VC-1, PACT; OVMM [208]
ALFRED [209]	-/120	84/84	-	Unity	Navi, Mani	RGB, D, S	PD	Human	Diverse long-horizon tasks	$(SL)^3$, LLM-Planner
DMC [210]	1/-	4/4	Code	MuJoCo	Control	RGB, D	Force	-	Continuous RL	VC-1, SMART
OpenAI Gym [211]	1/-	4/4	Code	MuJoCo	Control	RGB	Force	-	Single agent RL environments	-
Genesis [212]	(Rigid, deformable, liquid, etc.)		Code	(Proprietary)	Navi, Mani	RGB, D, S, N	Force	Franka, Unitree, etc.	High-speed comprehensive physics simulation	-

Challenges

- Real data is hard to get – robot demos take time
- Models are slow – need to act faster in real life
- System is complex – many parts must work together
- Struggle with new tasks – not good at generalizing
- No standard tests – hard to compare different models
- Safety is important – robots must be trusted by people

The Future of VLA Models

- Smarter planning with better world models
- Faster and smaller models for real-time use
- Use in homes, hospitals, factories, and more
- Safer and more human-friendly robot behavior
- Learn from the world just like humans do

Resources

Ma, Y., Song, Z., Zhuang, Y., Hao, J., & King, I. (2024). *A Survey on Vision-Language-Action Models for Embodied AI*. arXiv preprint arXiv:2408.14496. https://arxiv.org/abs/2408.14496