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An Enhanced Survey of Knowledge Representation in Robotics

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ABSTRACT: The absence of visualized datasets via data visualization is a problem that affects Unsupervised Learning of Robots. Robotics can be defined as a technological branch of artificial intelligence that is associated with the design and construction, operation and application of robots. Secondly, robots are designed for learning and performing complex tasks without human supervision. In this study, we developed an enhanced Robo-Earth Knowledge Representation Model for learning robots. Furthermore, we utilized Structured System Analysis and Design Methodology in this approach and further implemented with Statistical Package for Social Sciences (SPSS). The parameters for our result performance achieved an overall performance rate of 98% when compared with the Existing Robo-Earth Knowledge Representation Model. The parameters for the comparison included Time Complexity (TC), Life-Cycle Assessment (LCA), Benchmarking (B), Multi-Criteria Decision Making (MCDM), Risk Assessment (RA), Cost Benefit Analysis (CBA) and Speed (S) presented as TC, LCA, B, MCDM, RA, CBA, S = 25, 19, 7, 22, 6, 9, 10 respectively. In addition, the study recommended the vital importance of data visualization models in Knowledge Representation for learning robots.

KEYWORDS: Data Visualization, Knowledge Representation, Robotics, Robo-Earth

I. INTRODUCTION

Robotics belongs to a technological branch of artificial intelligence that is associated with the design and construction, operation and application of robots. Secondly, robots are designed for learning and performing complex tasks without human supervision (i.e. Unsupervised Learning).

The future expectation of robots encompasses products consumption. However, there is still a gap in terms of user expectations and robot functionality. An important factor to be addressed in robotics involves the development of models which trains the robots on problem-solving.

The focus of this paper dwells on the survey, design and development of a model for representing and visualizing knowledge for robots to assimilate and perform complex tasks. A Representation System converts different forms of knowledge to interpretable and visualized datasets in order to propagate common sense of reasoning. Furthermore, common types of knowledge propagated by a representation system encompass: Objects, Events, Procedures, Relations, Mental States and Metal Knowledge.

The absence of visualized datasets via data visualization is a problem that affects Unsupervised Learning of Robots. Furthermore, this problem is as a result of the following:

- i) Complex processes involved in modeling knowledge for robots to solve specific tasks
- ii) Complex processes involved in visualizing the knowledge for the robots to learn, understand and solve specific tasks

The aim of this study is to develop an enhanced model for representing knowledge to robots. The specific objectives of the study include:

- i) design an enhance model for representing data using Data Visualization Algorithm

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- ii) implement the proposed model with Statistical Package for Social Sciences (SPSS) as our proposed added tool to the Existing System in order to improve data visualization for robots
- iii) compare our results with the existing system performance

II. CONCEPT OF KNOWLEDGE REPRESENTATION

Knowledge representation is a unique process of representing information in order for proper understanding and problem solving. Secondly, human beings can understand better, reason better and further interprets knowledge better. Human beings are knowledgeable, and also apply their knowledge to solving various real-life problems. Hence we can describe Knowledge representation as following:

- i) Knowledge representation and reasoning (KR, KRR) is the part of Artificial intelligence which concerned with AI agents thinking and how thinking contributes to intelligent behavior of agents.
- ii) It is used for representing information about the real world so that a computer can understand and can utilize this knowledge to solve the complex real world problems such as diagnosis a medical condition or communicating with humans in natural language.
- iii) It is also a way which describes how we can represent knowledge in artificial intelligence.

There are several knowledge types represented by Artificial Intelligence Systems which include: Objects, Events, Facts, Knowledge-base

TYPES OF KNOWLEDGE

There are several types of knowledge that can be represented by artificial intelligence systems which include:

a) Declarative Knowledge:

Declarative knowledge can be defined as knowledge that includes concepts, facts and objects. It also uses declarative sentences to declare knowledge.

b) Procedural Knowledge

This type of knowledge can be defined as knowledge that promotes learning and assimilation of how to perform a given task. Furthermore, it is a type of knowledge that is dependent on the task it is applied on, and also encompasses strategies, procedures, agendas, etc.

c) Meta-knowledge:

This type of knowledge can be defined as information about the other types of knowledge.

d) Heuristic knowledge:

This knowledge can be defined as information that shows the knowledge of experts in specific fields.

e) Structural knowledge:

Structural knowledge is basic knowledge to problem-solving. It shows the union between several concepts of things.

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Figure 2.0: Types of Knowledge represented to AI Systems (Source: Java-Point, 2019)

RELATIONSHIP BETWEEN KNOWLEDGE AND INTELLIGENCE

Real-world knowledge is relevant and important in the area of artificial intelligence. In addition, most agents of Expert Systems show their intelligence through knowledge representation. An Artificial intelligence system has the following components for displaying intelligent behavior: Perception, Learning, Knowledge Representation and Reasoning, Planning and Execution

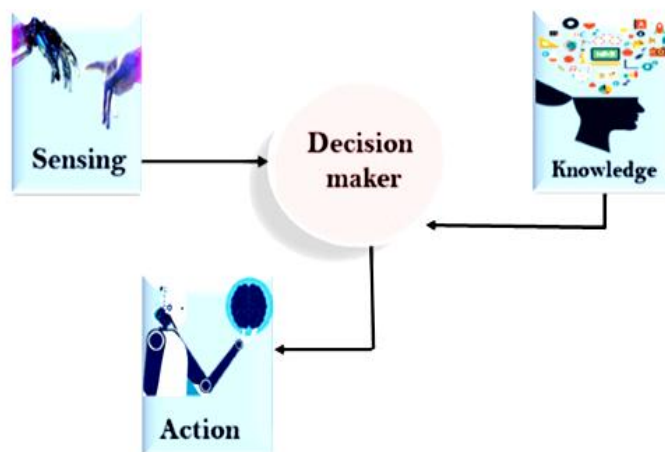


Figure 3.0: Sensing and Decision-making Structure for Artificial Intelligence Systems (Source: Java-Point, 2019)

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CONCEPT OF DATA VISUALIZATION FOR AN IMPROVED KNOWLEDGE REPRESENTATION IN ROBOTICS

Visualization of data in robotics is an enhanced technique for Knowledge Representation. When information is interpreted in forms of charts, diagrams, animations and patterns, it is said to be Data Visualization.

According to Mir et al (2019); “Data Visualization is needed to interpret metabolomics data of humans. This has been achieved through metabolomics technologies. However, there is still room for improvement via modernized data visualization tools.

According to Joe et al (2019); “Surveys often require monitoring during data collection to ensure progress in meeting goals or to evaluate the interim results of an embedded experiment. Complex designs always involve time-consuming and overwhelming production process”

IV. RELATED WORKS

Shu et al (2019) looked at Geographic Knowledge Graph (GeoKG): A formalized geographic knowledge representation. The study analyzed representation of knowledge in form of geographical charts for efficient visualization of data. However, the authors could not include the visualization of knowledge graph using a Geographic Information System.

Franz et al (2019) researched on Matching in the Description Logic with respect to General T-Boxes. The authors described matching as a special case of unification where one of the expressions to be unified has no variables and thus, remains unchanged under substitution. They further developed a model for matching description and T-boxes. However, they could not carry out performance evaluation of their model with other existing models, especially in areas of Life Cycle Assessment (LCA) and Pattern Recognition (PR).

David et al (2019) looked at a survey of knowledge representation in service robotics. The study illustrated knowledge representation models that are based over the cloud, and their roles in benefiting robot learning. However, the authors could not implement a data visualization layer for their proposed model.

Freddy et al (2019) looked at the role of Knowledge Graphs in Explainable AI. The study reviewed the concepts of Explainable AI (XAI) not only from a Machine Learning perspective, but also from other AI research areas such as AI planning or constraint satisfaction and search. The authors further exposed XAI challenges of AI fields, their opportunities for knowledge graphs and their underlying technologies. However, they could not implement with a model and programming language.

V. ANALYSIS OF THE EXISTING SYSTEM

David et al (2019) researched on a survey of knowledge representation in service robotics. They further proposed a KR model called Robo-Earth (see figure 4.0). The proposed model illustrates knowledge representations that are based over the cloud. Robo-Earth is referred to as the “World Wide Web for robots”. It is an ongoing collaborative project aiming to create a cloud-based database for robots to access knowledge needed to solve a task. Robo-Earth was first proposed as a proof-of-concept to show that cloud robotics would greatly simplify robot learning. Robo-Earth provides ontology for storage of semantic concepts and a method for accessing knowledge through software as a service (SaaS) inter-face, where computational inferences and mappings can be done remotely. As a collaborative system, Robo-Earth allows robots to archive its own experiences (such as object types observed, motion plans successfully or unsuccessfully used, robot architectures, etc.) for recall and re-use by other capable robots. This database would contain massive amounts of data (in the form of object models, SLAM maps, semantic maps, etc.) which can be used for tasks such as object recognition, instance segmentation and path-planning.

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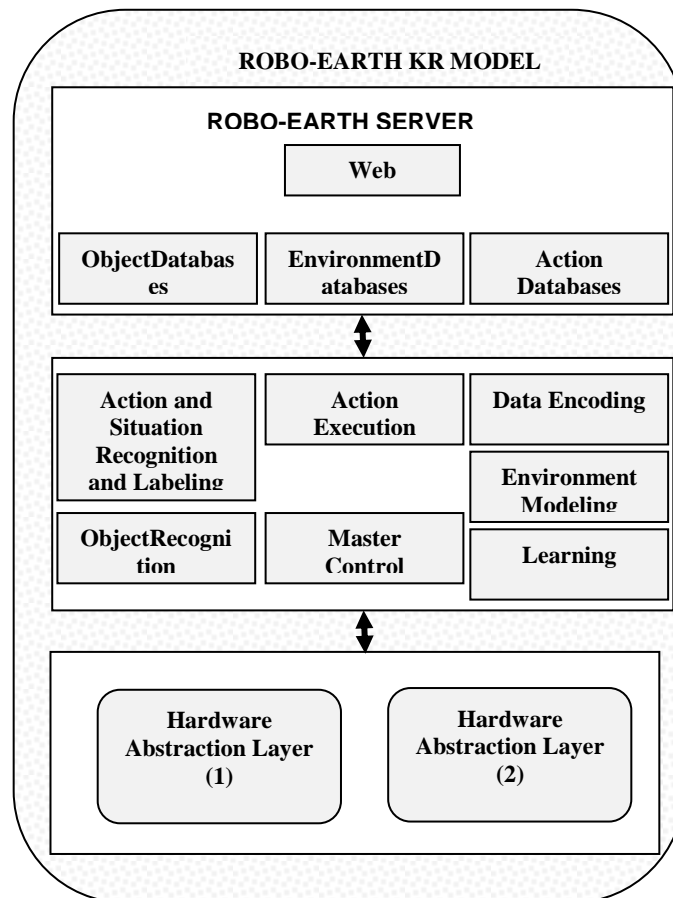


Figure 4.0: Robo-Earth KR-Model (Existing System Architecture) (Source: David et al, 2019)

3.2 ANALYSIS OF THE PROPOSED SYSTEM

We further improved the Existing System Architecture through the addition of a Data visual layer which would improve the Knowledge Representation Output of the Mode (see figure 5.0). The improved layer is implemented with Statistical package for Social Sciences (SPSS). The implementation tool further enhances representation output in form of charts, patterns and diagrams.

Before beginning data collection, it is important to define what “success” means for the aims of a particular survey. This often involves discussing the study goals with the survey sponsors and data collection team to identify which metrics are most important to track and which combination of values will indicate whether the goals have been met. Metrics can be related to quality, cost, schedule, or other dimensions and can be constructed in myriad ways. Key to monitoring data collection is determining how best to track progress toward project-defined goals.

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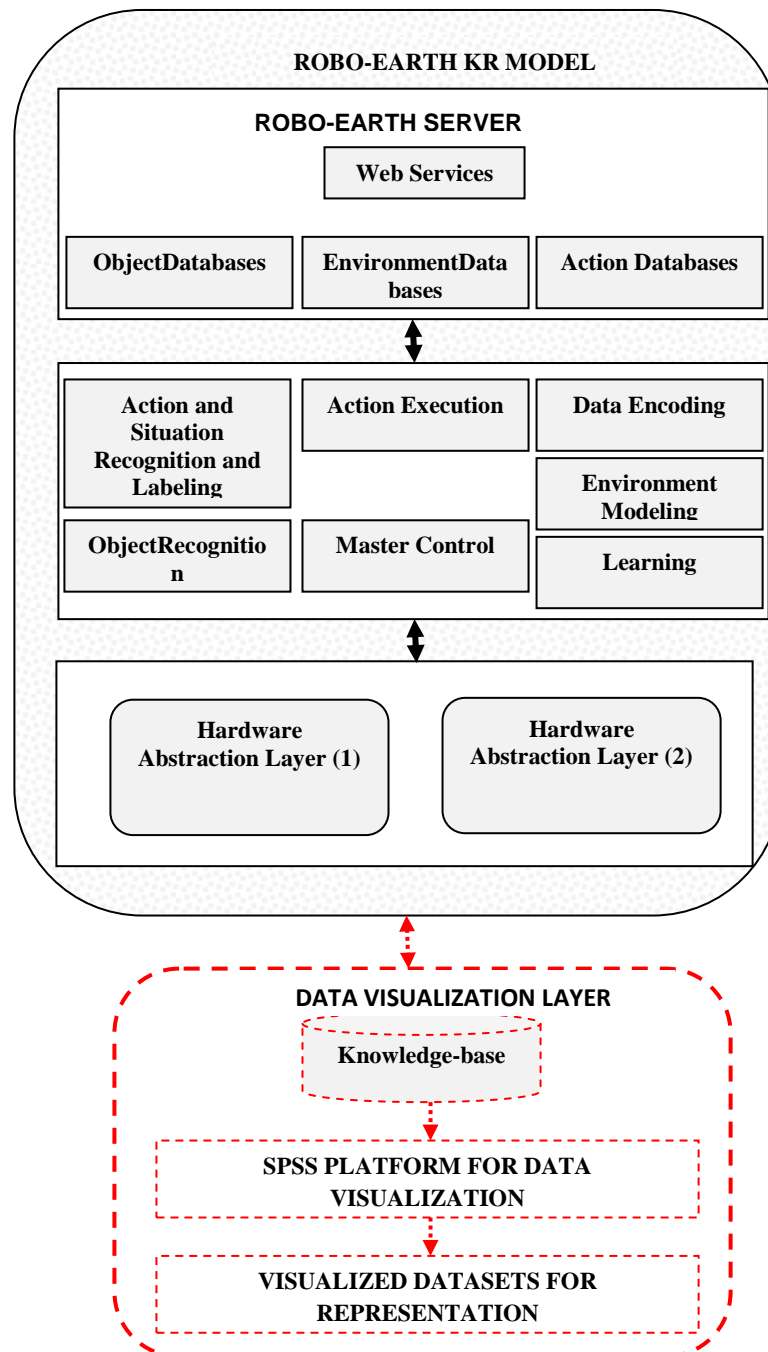


Figure 5.0: An Enhanced Robo-Earth KR-Model
(Proposed System Architecture)

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V. METHODOLOGY

Our adopted methodology is Structured System Analysis and Design Methodology (SSADM)
The Methodology application to the proposed system involved the following stages:

i) Stage One:

Analyzing Existing ways deployed to tackle the issue:

There was in-depth analysis on current performance of the Existing System in Recommending reliable information to users.

ii) Stage Two:

Existing System Performance and Identification of Anomalies:

This phase involved studying result performance of the Existing System in order to spot any anomaly that should be corrected.

iii) Stage Three:

Review of any spotted anomaly from the Existing System:

This phase involved the deployment of the proposed system algorithm to any spotted anomaly from the Existing System Performance.

iv) Stage Four:

Comparison of the Existing and Proposed Systems Performance Result: This phase involves comparing results of the Proposed and Existing Systems Performance.

v) Stage Five: This phase involves the adoption of the most efficient result that tackles the mentioned issue due to the outcome of the comparison between the Existing and Proposed Systems.

ALGORITHM FOR THE PROPOSED SYSTEM FUNCTION

STEP 1: START

STEP 2: DECLARE VARIABLES;

EREKR, UN, PW, RES, GC, SP, DVL, VUA

WHERE

EREKR = ENHANCED ROBO-EARTH KNOWLEDGE REPRESENTATION,

UN = USERNAME

PW = PASSWORD

RES = ROBO-EARTH SERVER

GC = GENERIC COMPONENTS

SP = SPECIFICATIONS

DVL = DATA VISUALIZATION LAYER

VUA= VALIDATE USER ACCESS

STEP 3: INITIALIZE VUA

STEP 4:

VUA = UN + PW

STEP 5: ACTIVATE RES FOR ROBOT LEARNING

STEP 6:

RES = (GC + SP)/DVL

STEP 7:

OUTPUT CONTENT OF DVL TO ROBOT

STEP 8:

STOP

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VI. RESULTS

Our adopted approach for knowledge representation produced high level representation of tasks using scalable knowledge bases. Furthermore, after carrying out comparative analysis of our system with the existing system performance; the evaluation of our improvement was measured based on the following criteria:

- i) Speed (S)
- ii) Time Complexity (TC)
- iii) Life-Cycle Assessment (LCA)
- iv) Multi-Criteria Decision Making (MCDM)
- v) Risk Assessment (RA)
- vi) Cost Benefit Analysis (CBA)
- vii) Benchmarking (B)

Table 1.0: David et al (2019): Robo-Earth (RE) Knowledge Representation Model

SN	PERFORMANCE EVALUATION CRITERIA (PEC)	ASSESSED PERFORMANCE RATE (%)
1.	Time Complexity (TC)	21
2.	Life Cycle Assessment (LCA)	13
3.	Benchmarking (B)	7
4.	Multi-Criteria Decision Making (MCDM)	22
5.	Risk Assessment (RA)	4
6.	Cost Benefit Analysis (CBA)	8
7.	Speed (S)	10

Assessed Parameters Summary:

TC	=	21
LCA	=	13
B	=	7
MCDM	=	22
RA	=	4
CBA	=	8
S	=	10
TOTAL	=	85%

Table 2.0: Vivian (2019): An Enhanced Robo-Earth (RE) Knowledge Representation Model

SN	PERFORMANCE EVALUATION CRITERIA (PEC)	ASSESSED PERFORMANCE RATE (%)
1.	Time Complexity (TC)	25
2.	Life Cycle Assessment (LCA)	19
3.	Benchmarking (B)	7
4.	Multi-Criteria Decision Making (MCDM)	22
5.	Risk Assessment (RA)	6
6.	Cost Benefit Analysis (CBA)	9
7.	Speed (S)	10

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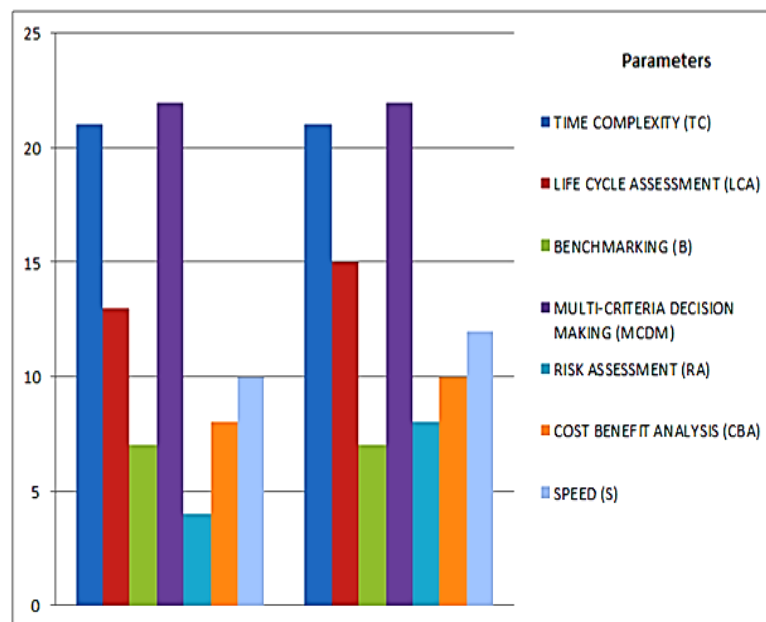
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Assessed Parameters Summary:

TC	=	25
LCA	=	19
B	=	7
MCDM	=	22
RA	=	6
CBA	=	9
S	=	10
TOTAL	=	98%

Figure 6.0: Comparative Analysis Chart of the Proposed System against the Existing System



VII. CONCLUSION

This study critically surveyed the best possible model for representing knowledge in robotics. Robotics is part of the technological future of Artificial Intelligence and Expert Systems. How robots solve complex tasks will depend on how unique the information about solving the task is interpreted to them. In other words, the need to visualize data as part of Knowledge Representation is highly indispensable.

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