2022 European Conference on Computing in Construction
Ixia, Rhodes, Greece
July 24-26, 2022

DEVELOPMENT OF DIGITAL TWIN MODELS SUPPORTING AMBIENT ASSISTED LIVING

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Abstract

World population aging requires finding solutions to improve independent living options. Ambient Assisted Living (AAL) is making step forward developing services supporting the elderly, but the implementation of predictive environments is still far away.

Besides, the emerging Digital Twin (DT) concept has begun to shape the first cognitive environments that integrate users into assessments, improving efficiency, prevention, and prediction of likely events through real-time AI computing.

This paper provides a prototype of a Cognitive Building framework based on DT models that develop high-level knowledge to achieve real-time Scenario Awareness and offer appropriate AAL services once anomalous scenarios are detected.

Introduction

The age span of elderly people is currently increasing, and this trend is going to last in the future. UN assessed the number of people aged 65 years or over were slightly more than 700 million in 2019, and this number is currently growing sharply. It is indeed projected to double by 2050, reaching 1.5 million people (United Nations, 2020a) (United Nations, 2020b). The impact of the aging population has direct consequences on the elderly lifestyles. The increase in number of people aged over 65 directly affects the share of the population suffering from cognitive disorders. The occurrence of such mental diseases makes the elderly in need of assistance owing to loss of autonomy (Berryhill, et al., 2012). Enhancing autonomy regardless of an elderly person's level of capacity can be achieved through a range of processes, including advanced care planning, supported decision-making and access to appropriate assistive devices (World Health Organization, 2017).

AAL is developing products and technological services as solutions to foster the environments inhabited by older people, leveraging state-of-the-art technologies (Dobre, et al., 2017). Nevertheless, these solutions are far from predictive environments as intended by the AAL policies declared in (World Health Organization, Regional Office for Europe, 2017). Whereas a plethora of products that help users achieve specific objectives is available, there is a lack of comprehensive building-level solutions.

DTs represents an opportunity to accomplish AAL policies. To that end, this paper provides prototypes of DT models to automatically detect anomalies within an AAL context and offer support to the user in case of need.

Background

Ambient Assisted Living

AAL is defined in (Dobre, et al., 2017) as *"an emerging multi-disciplinary field at the intersection between information and communication technologies, sociological sciences, medical research, that aims to develop personal healthcare and telehealth systems for countering the effects of growing elderly population"*. The home environment can have a significant influence on AAL's purposes. It provides a range of resources or barriers that will ultimately decide whether older people can engage in activities that matter to them. Developing or maintaining the functional ability pursuing Activities of Daily Living (ADLs) enables autonomous well-being in older ages. In this regard, some of the main objectives of AAL are encouraging, supporting, and easing the elderly in their ADLs. Currently, AAL products that support the elderly's autonomy include assistive robots, smart home applications, smart wheelchairs, and interactive applications for social inclusion and communication (Li, et al., 2015). Those tend to define age-friendly environments which intrinsically help users supporting their ADLs. Nevertheless, WHO's prospects for achieving context-aware environments seem distant (World Health Organization, Regional Office for Europe, 2017). Innovation in construction by means of DTs could narrow the gap.

Digital Twin in Ambient Assisted Living

A number of DTs have already begun to appear within the built environment, serving a variety of purposes depending on domains (Sharma, et al., 2020) (Opoku, et al., 2021) (Liu, et al., 2021). A building-level DT is a tool that can enhance efficiency, prevention, and prediction of likely events during the whole building's life cycle. The DT's concept lies on data-driven frameworks. It goes beyond the common concept of Smart Buildings, defining cognitive and responsive environments that are called

Cognitive Buildings (CBs) (Yitmen, et al., 2021). Those consider both the environment and its users processing real-time information to offer tailored services.

The growing interest in the AAL domain has enabled the development of state-of-the-art CB systems for human-centered home environments (De Paola, et al., 2017) (Rafferty, et al., 2017) (Calderita, et al., 2020) (Patel & Shah, 2020). Those are able to learn at scale, reason with purpose and co-operate with users in a natural way. They learn and reason from the interactions with both the users and the environments where they are deployed, evolving with them, and running "What if?" scenarios for predicting anomalies and behaviors. Although the aims of DTs in AAL can vary widely, one of the most crucial tasks is detecting ADLs, and consequently anomalous/dangerous activities. Usually, these systems monitor the users employing different types of components such as IoT devices or other sensors. Those basically make feasible a collection of data that are further processed through Artificial Intelligence (AI) models to extract both environmental features and user's behaviors and conditions. Advanced systems deploy multi-modal sensors (e.g., sensors that define time patterns combined with accelerometers), whereas others are based only on just one kind of signal (e.g., accelerometers). Nevertheless, the use of visual sensors (e.g., cameras or LiDAR) in this field has only recently emerged due to the progress of technologies such as Convolutional Neural Networks (CNN) that facilitate the computation of visual data.

Prototyping a CB supporting AAL environments means developing a system that can cope with complexity, randomness, and uncertainty in real-time: understanding the unpredictable nature of the intentions of a person suffering from cognitive disorders to offer proper support first requires knowing (mirroring) the interactions with the elements in the context, the activities undertaken, the habits and feelings, and if everything matches what he or she is actually saying or doing. Accordingly, the following methodology is meant to define a layered system consisting of multiple intelligent agents that contributes to outlining the required functionalities:

- Data acquisition through visual and non-visual sensors.
- Integrated real-time scenario representation that combines information from multiple domains.
- Recognition of the activities performed by the user.
- Situation and scenario awareness (i.e., contextualization of basic information).
- System-user bidirectional interaction.

Methodology

Real-time 3D Representation

Digital Twins mirror real environments creating virtual instances of the asset and the user. Thus, a consistent representation of the context cannot be defined by building elements only. For this reason, Building Information Modeling (BIM) is combined with a real-time user representation within a real-time programmable platform (Unity).

Firstly, BIM represents a reliable basis for a building-level DT as it provides a detailed description of the building elements and may become essential as the purposes of the DT will eventually expand. BIM objects can also be associated with dynamic features (e.g., appliance On/Off states, environmental temperature, and so forth).

Secondly, the user virtual representation is synthesized through its posture, which is typically referred to as *Skeleton*. The real-time Skeleton of the user is generated by a Skeleton tracking algorithm (Nuitrack AI) that processes 3D information that comes from a LiDAR camera (Intel RealSense L515). Since the Skeleton does not define a complete semantic of the user, other information such as the activities that he or she performs need to be extrapolated.

Activity Recognition

There are two main approaches for Activity Recognition (AR), namely data-driven and knowledge-driven (Rafferty, et al., 2017). The first approach consists in exploiting datasets to learn models of daily activities through probabilistic and statistical methods (e.g., implicit data mining models such as Artificial Neural Networks). Data-driven models enable the modeling of uncertainty but require suitable datasets. On the contrary, the second approach is based on domain knowledge, which is an intuitive record learned through people's experiences, and deductive heuristics as the foundations to produce activity models (e.g., logic-based and ontological approaches). Knowledge-driven models do not rely on datasets but cannot deal with uncertainty.

Since an extensive sampling of data concerning the recognition of activities performed by individuals is available nowadays, a data-driven approach is followed by means of a Neural Network (NN) model. Nevertheless, it is essential to make a distinction between two types of activities that the user might undertake:

- Activities that produce a visible effect when they are completed (e.g., wearing a jacket).
- Activities that do not produce a visible effect when they are completed (e.g., drop something).

While the first kind of activities might also be detected by Object Recognition NN models, the second kind of activities is more difficult to classify without training the NNs on human activity datasets.

The *MS-G3D* model, developed in (Liu, et al., 2020) is integrated in the presented system. It is based on the Spatial-Temporal Graph Convolutional Networks (ST-GCNs) proposed in (Yan, et al., 2018) and on the Two-Stream Adaptive Graph Convolutional Network (2s-AGCN) proposed in (Shi, et al., 2019). This kind of NN models does not rely on RGB images or videos, as the earlier CNN models did, but consider the joints of the Skeleton as graphs, exploiting their 3D coordinates. This allows for light-weight models. To sum up, the MS-G3D model is selected for the following reasons:

- Pre-trained on human activity datasets
- Exploits 3D Skeleton information
- Light-weight system
- Outperforms existing methods for AR by a sizable margin on the three most common large-scale datasets

Scenario Awareness

Information about the user's location, posture, activity, and behavior and BIM data define a low-level knowledge on the real asset of its virtual counterpart. Therefore, low-level information needs to be contextualized to develop a higher level of knowledge reaching an awareness of what is happening within the environment in real-time. This could be achieved formalizing a model that is referred to as *Reasoner*. Its requirements are the following:

- *Scalability*, the Reasoner must adapt to real-world environments where conditions and constraints may vary.
- *Accessibility*, the Reasoner and its parts have to be open and accessible. Implicit models would not be suitable for this role.
- *Reusability*, although situations (homes, environments, and users) may be different and may change depending on numerous variables, AAL scenarios all have similar aspects. Therefore, the model must have the capability to adapt to other scenarios without dramatic modifications.

This task could be carried out by following at least two different approaches:

1. Rule-based
2. Probabilistic

The first approach uses rule-based algorithms that could be written depending on the services needed. Rules are usually if, else conditions. A rule-based reasoner has been proposed in (De Paola, et al., 2017). Their module is fed with the output of an AR module (in that case, the detection of the activities is performed by a Bayesian Network) and takes basic decisions such as turning the heating/cooling system On or Off and recognizes some health anomalies. Although rules concerning anomalies could be found, they are not always easy to express. Moreover, when considering an elderly person suffering from cognitive disorder, defining strict or complex rules may become extremely challenging. The scalability and reusability requirements would not be met. For these reasons, the second approach seems to be the most effective. A probabilistic model is based on conditional probabilities that an event may occur depending on evidence or other variables.

In this work a Bayesian Network (BN) is formalized to act as the Reasoner of the system. BNs are probabilistic graphical models that represent a set of variables and their conditional dependencies via a directed acyclic graph. Expert knowledge could be elicited in Conditional Probability Tables (CPTs) of the nodes that represent the events. BNs are ideal for taking an event that occurred and predicting the likelihood that any one of several possible known causes was the contributing factor (De Grassi, et al., 2009). In our case, BNs should be able to infer different types of anomalies:

- Anomalies that define wasteful situations (e.g., window open while heating system is on).
- Anomalies that derive from senseless behaviors (e.g., skipping meals).
- Anomalies that define dangerous situations (e.g., something dropped on the ground).
- Emergencies (e.g., falls).

System-user bidirectional interaction

Since the system aims at supporting the user ADLs, it should be equipped with a range of applications to deliver appropriate services. Hence, a Dialog System that allows a bidirectional vocal interaction between the system and the user is implemented.

The conversational agent is built exploiting a Flow-Based Programming (FBP) tool. FBP is a programming paradigm that shapes applications as networks of black box processes, that exchange data across predefined relations by message passing, Relations are specified externally to the processes. These black box processes can be rewired endlessly to form different applications without having to be modified internally.

Node-RED is a FBP tool that allows users to create applications by manipulating program elements (black boxes) graphically rather than by specifying them textually. Node-RED enables hardware devices, Application Programming Interfaces (APIs) and online services to be wired together within a browser-based editor. Thus, this platform can also bridge the gap between the Reasoner and the services that the system provides. Applications can be built by dragging nodes from palettes into a workspace and wiring them together. Then, the application can be deployed. The palette of nodes can be easily extended by installing new nodes created by the community.

System Architecture

Firstly, the requirements the system should meet are defined:

- *Modularity*, system's agents should be modifiable or replaceable to allow the integration of models that could be more appropriate to the intended purpose.
- *Flexibility*, it regards the system capability to adapt to the user and learn over time the changing habits to act accordingly.
- *Non-intrusiveness*, systems that imply monitoring the subject is generally not easily accepted by the individual. The awareness of being observed is perceived as a discomfort. For this reason, it is essential for the system's components to be as less intrusive as possible. Hence, it is very important not to interfere too much with the user's ADLs: interactions should not be perceived as invasive.
- *Affordability*, low-cost is a key requirement whether the system is deployed in a private home or in a healthcare structure.

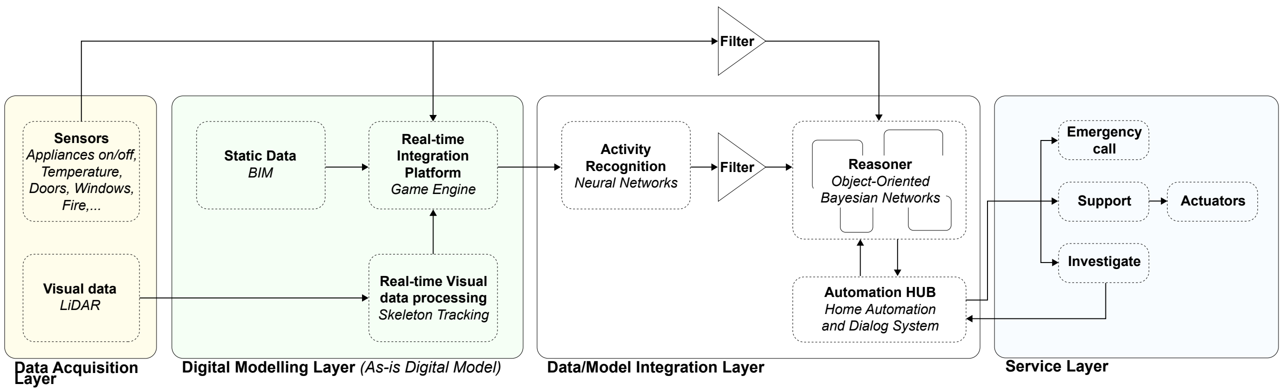

Figure 1: System architecture. Arrows indicate data flow (Transmission Layer).

Then, the system architecture of our prototype is outlined following the guidelines stated in (Lu, et al., 2020), which defines the structure of a building-level DT. Thus, the presented model consists of five layers, namely Data Acquisition Layer, Transmission Layer, Digital Modelling Layer, Data/Model Integration Layer and Service Layer. Its pipeline defines a system able to autonomously perform high-level reasoning to detect anomalies in daily scenarios and consequently offer support to the user. Figure 1 shows the architecture of the proposed system.

Data Acquisition and Digital Modelling Layers

Data Acquisition and Digital Modelling layers hold the computation used to manage the 3D real-time representation of the context. A virtual scenario is created. It contains both the home environment, described by BIM data, and the avatar of the user, built upon its Skeleton. Adjustments are required within the real-time integration platform.

A first level of filtering is applied to the confidence of the Skeleton joint's data. Some joints may have low confidence values, meaning that they are not extremely reliable. Non-natural joint positions would lead to distortions of the avatar and bias. Thus, a confidence threshold is introduced with a value of 10%. Less confident joints are discarded.A second level of filtering is implemented to enhance the Skeleton stabilization, based on the following autoregressive filter:

$$X_{(t+1)} = (1-a) \cdot X_{(t)} + a \cdot X_{(t+1)}^{raw} \qquad (1)$$

where $X_{(t+1)}$ is the processed data at the time $(t+1)$, $X_{(t)}$ is the processed data at the time (t), a is a corrective factor with a value that ranges between 0 and 1, and $X_{(t+1)}^{raw}$ is the raw value of the data at the time $(t+1)$. This filter is applied to three features of the avatar: height, joint position, and joint orientation. Since a is close to 0, the value at the time $(t+1)$ is close to the value at the time (t), defining more consistent and natural movements, without the ambiguities the avatar had before. Cleaner avatar's movements result in cleaner output data that will consequently feed the NN model.

Besides, since the system includes the MS-G3D model, which is pre-trained on the NTU RGB+D dataset (Shahroudy, et al., 2016), the avatar joints are remapped as the Kinect v2 Skeleton (used to build the NTU dataset). Then, the Feature Vector is exported, expressed as a spatial-temporal tensor $\mathbf{X} \in \mathbb{R}^{T \times N \times C}$. $\mathbf{X}$ is the input to the MS-G3D model and includes the number of joints (N) and their relative coordinates (C) throughout the time (T).

Algorithm 1 Skeleton stabilization

Input: Joints data from the skeleton tracking algorithm
Output: Stabilized avatar

```
Find Skeleton, define weights and threshold:
  float a = 0.02f;
  float t = 0.2f;
  float threshold = 0.1f;
if confidence ≥ threshold then
Get avatar joint: avatarJoint = joint.Value;
  Find height: differences of joint's z-values
  Apply filter to height:
    height = (1-a) * height + a * newHeight;
  Scale avatar to match human height:
    targetGameObject.transform.localScale =
    new Vector3(height/1.80f, height/1.80f,
    height/1.80f);
  Calculate the model position:
    Vector3 rootPos = Quaternion.Euler(0f, 180f,
    0f) * (0.001f *
    skeleton.GetJoint(rootJoint).ToVector3());
  Apply filter to position:
    transform.position = (1-t) *
    transform.position + t * rootPos;
  Calculate the model bone rotation:
    Quaternion jointOrient =
    Quaternion.Inverse(CalibrationInfo.SensorOr
    ientation) *
    (jointNuitrack.ToQuaternionMirrored()) *
    avatarJoint.baseRotOffset;
  Apply rotation to bone based on the detected
  skeleton:
    avatarJoint.bone.rotation =
    Quaternion.Slerp(avatarJoint.bone.rotation,
    jointOrient, t);
end if
```

Data/Model Integration Layer

Data/Model Integration Layer is responsible for analyzing and processing the data, collected and fixed by the previous layers. Hence, its accuracy influences the

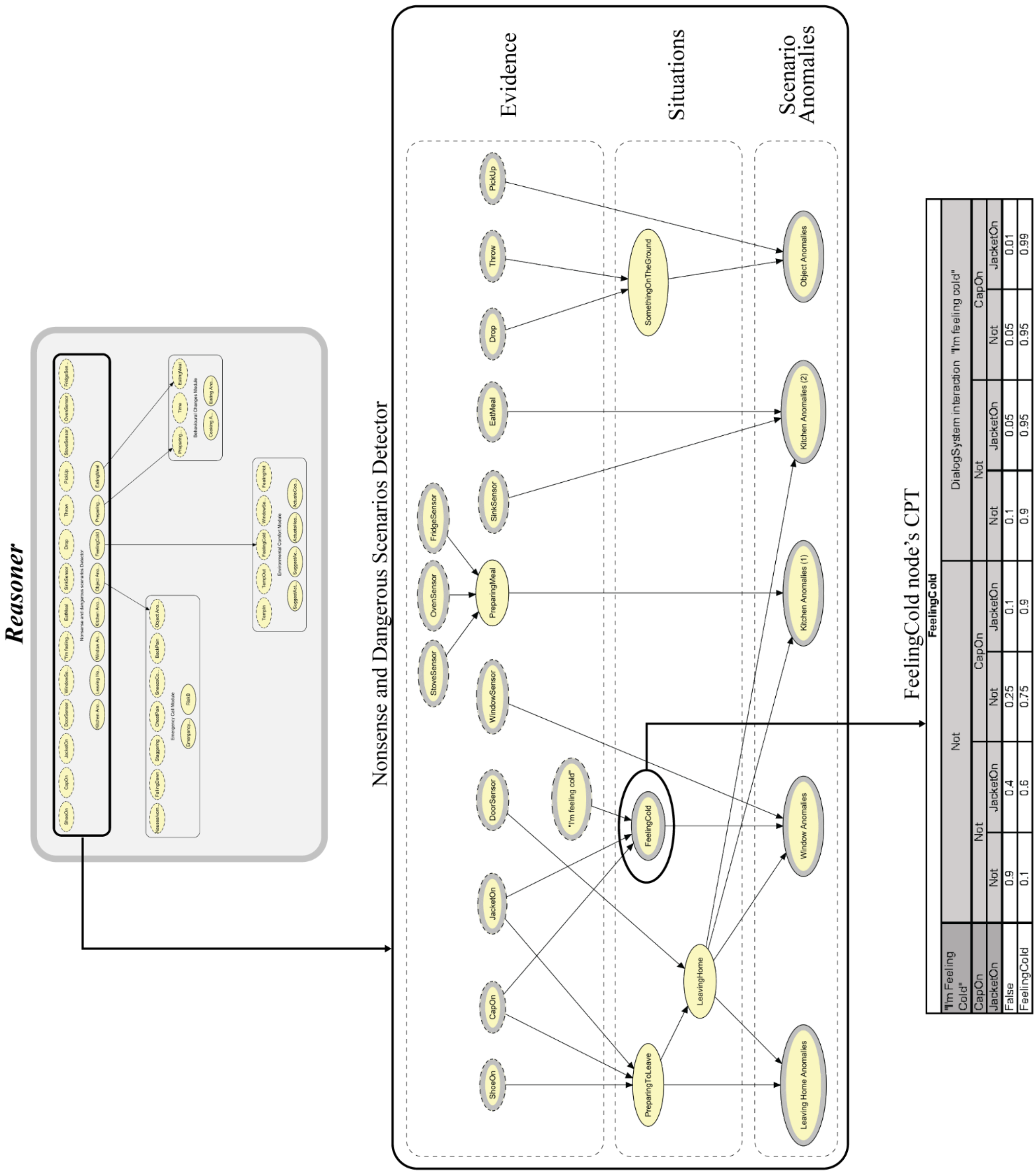

Figure 2: The Reasoner consists in an Object-Oriented Bayesian Network, decomposed in turn into four underlying OOBN modules. Zooming in shows the Nonsense and Dangerous Scenarios Detector module and the CPT of the "FeelingCold" situation node. Dashed gray edged nodes represent input nodes. Solid gray edged nodes represent output nodes.

effectiveness of the decision-making process. This layer consists of three intelligent agents that can detect the activities performed by the user, reason on the current scenario to detect anomalies, and act accordingly to support the individual.

Reasoner

This unit is formalized as an Object-Oriented Bayesian Network (OOBN) (Figure 2), composed in turn of four deductive OOBN modules that aims at detecting the anomalies previously described:

1. Nonsense and dangerous scenarios detector
2. Behavioral changes detector
3. Environmental comfort module
4. Emergency module

Firstly, the followed approach considers general symptoms that could lead to anomalous scenarios such as confusion, depression, loss of memory, emotional distress and difficulty paying attention (Berryhill, et al., 2012) (Dillon, et al., 2013) (scie.org, 2020). Then, a new semantic regarding probable events, situations, scenarios, and anomalies in AAL environments is built to formalize

the networks. Evidence is captured by sensors (turning on/off appliances, indoor/outdoor temperature, open/closed window, and so forth). Similarly, AR model results and voice interactions between user and system are considered evidence as well. Situations are combinations of evidence and represent feelings, behaviors, events, or intentions (feeling hot/cold, getting dressed, something on the ground, leaving home, and so forth). By associating and combining available evidence and recognizable situations, probable scenarios are theorized as the anomalies that may occur. Anomalous scenarios therefore include time disorientation, organizational problems, indifference to the environment, getting easily overwhelmed, mishandling appliances, changes in eating patterns.
This approach allows the contextualization of low-level information defining an explicit model.

Dialog System

The Data/Model Integration Layer includes an Automation HUB, based on Node-RED, that can integrate applications to offer appropriate support to the user. Since it is responsible for communications among different components of the system, this module could also be defined as a *Broker of Messages*.
In this paper, a Dialog System is implemented as one of the possible supportive applications. Services that rely on Machine Learning methods are integrated to establish a Dialog System whereby bidirectional interactions between the user and the cognitive layer of the building can be performed (Figure 3). Specifically, the IBM Watson palette of nodes is exploited. It offers Speech-To-Text (STT) and Text-To-Speech (TTS).

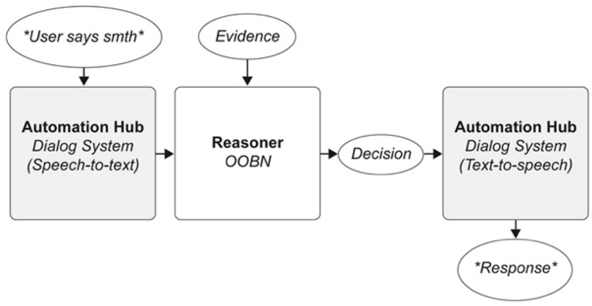

Figure 3: Interactions between the Reasoner and the Broker of Messages.

System Implementation

Virtual Environment Development

The combination between BIM and Skeleton information allows achieving a reliable real-time virtual representation of the physical asset which is shown in Figure 4.
BIM data from a home environment are converted to Industry Foundation Classes (IFC) format using Autodesk Revit. Importing IFC files into the Unity game engine recognizes all BIM objects as Prefabs. Prefabs preserve information from BIM objects. Working with physics engines, Unity allows additional properties to be assigned to Prefabs, achieving greater realism and consistency. Accordingly, mesh collider attributes is applied to tangible components to avoid inconsistencies with the avatar. Additionally, dynamic features can be added to Prefabs to include real-time sensor readings related to BIM objects. In this regard, activation, proximity, and environmental sensors are considered in this work to collect information respectively about the appliances (oven, stove, and fridge) and kitchen sink, the entrance door and a window, and the environment (indoor and outdoor temperatures).
Regarding the Skeleton testing, the LiDAR camera is placed at a height of 1 meter and leveled horizontally. The tests show that the distance between the user and the camera should be unobstructed and not exceed 5 meters to obtain consistent results.

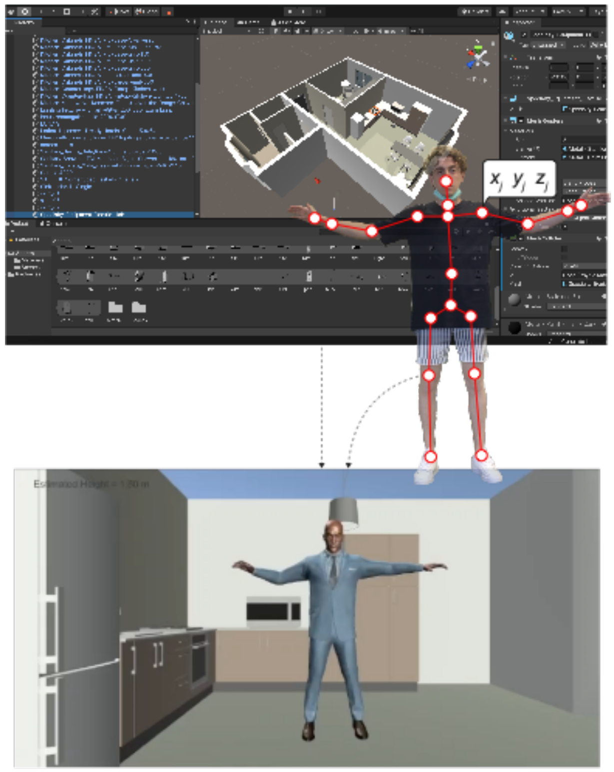

Figure 4: Results of the real-time 3D representation of the context build upon BIM data and the Skeleton.

Reasoner prediction

To evaluate the effectiveness of the Object-Oriented Bayesian Networks developed in this work, the node's CPTs are filled eliciting the knowledge of the authors. Figure 2 shows the CPT relative to the "FeelingCold" situation node. Besides, probability tables regarding input nodes are left unspecified since the network is not fed with data retrieved from a real-world environment. Thus, their relative tables are filled with total uncertainty values (i.e., 50%). Then, possible combinations of evidence are set up by manually activating input nodes. This helps demonstrate the consistency of the different decisions taken by each OOBN module. It is worth noting that the anomalous scenarios this work proposes do not depend on the types of room. These considerations are left for future developments. Accordingly, the Door and Window evidence nodes are related to sensors respectively applied to the entrance door and the living room. Following the provision of evidence in the modules, the expected consequences achieve high percentage values meaning that predictable anomalies within the scenario are fully recognized.

Figure 5 shows an example of anomaly detection within the Nonsense and Dangerous Scenario Detector. Four input nodes are manually set up to represent a scenario where the user is barefoot, not wearing a jacket and hat, and is opening the door. Specifically, the ShoeOn, CapOn, and JacketOn input nodes are set up to false (activities recognizable through the AR model), while the DoorSensor input node is set up to open. The user is not preparing to leave (98,90% false) but is actually leaving home (90,09% true). The "Leaving Home Anomalies" output node detects a likelihood of 87,34% that the user is leaving undressed.

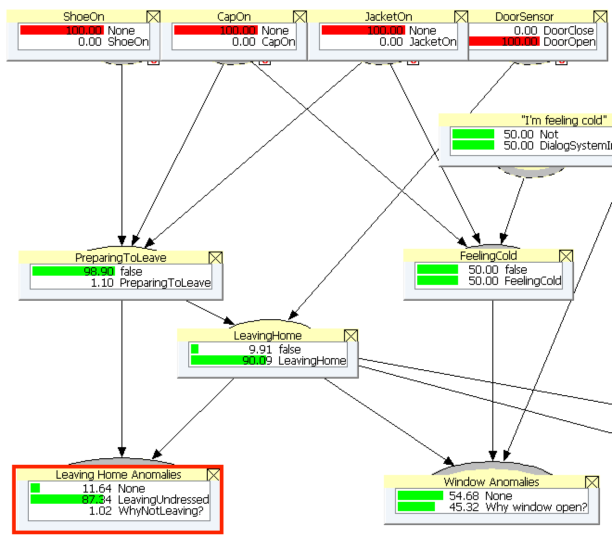

Figure 5: Detected anomaly within the Nonsense and Dangerous Scenario Detector.

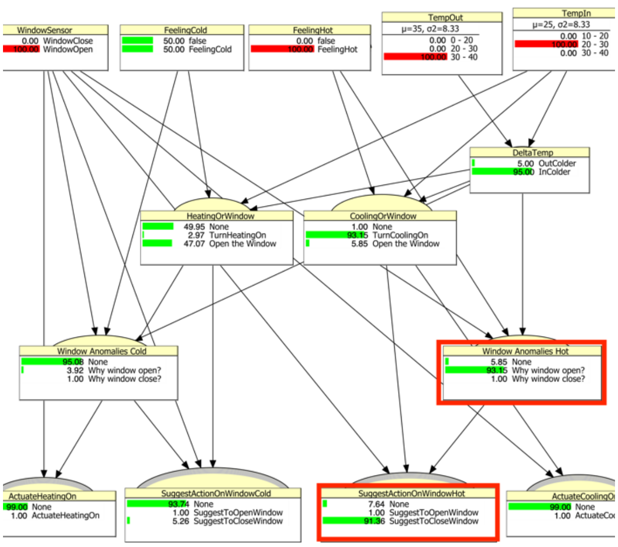

Figure 6: Detected anomaly within the Environmental Comfort Module.

Figure 6 shows an example of anomaly detection through the Environmental Comfort Module. This setup represents a scenario where the outdoor temperature (set to a range of 30 to 40°C) is higher than the indoor temperature (set to a range of 20 to 30°C), the user is feeling hot, and the window is open. Note that since the BN is Object-Oriented, the activation of the "FeelingHot" node, that belongs to situation nodes, is triggered by the activation of input nodes into other modules of the network (e.g., vocal interaction, undressing activities, and so forth). The module recognizes the window anomaly (93,15%) and suggests closing the window to avoid waste instead of turning on the cooling system.

System-user interaction implementation

The prototype of Dialog System is built upon the STT and TTS processes (Figure 7). On the one hand, STT process starts by recording the user's speech through a microphone, integrated in the editor through the microphone node. Here, Hot Phrases (HP) are not required (HP are those typically used to trigger common Dialog Systems such as Alexa and Google Assistant). Is essential not to have HP since the user may forget them due to cognitive impairments. Then, the record is sent to the IBM's Watson STT service that processes the input data returning a transcription of the speech. Finally, the transcription is shown in the Node-Red's debug tab.

On the other hand, TTS process is automatically triggered by the system depending on the output of the Reasoner. Tailored messages can be played depending on the needs of the user. These written messages are converted through the IBM's Watson TTS service. Finally, the converted speech is played by the integrated speakers.

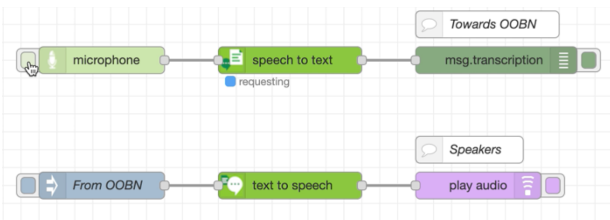

Figure 7: SST and TTS processes within the Node-RED editor.

Conclusion

The focus of this work lies in developing a CB system that supports AAL. Since the number of the elderly and, consequently, geriatric diseases such as cognitive disorders are increasing, a building-level DT in AAL scenarios offers solutions to support people in their older age. The end goal of the system is improving the quality of life of elder people, by preserving their autonomy whilst ensuring their safety. The grounded multi-agent system architecture defines a model able to autonomously perform real-time high-level reasoning, that allows the detection of anomalies in daily scenarios, and consequently offers support to the user. The strength of this architecture lies in the development of knowledge: from raw data captured by multi-modal sensors (visual and non-visual) and their real-time 3D representation into the virtual counterpart, to high-level reasoning and decision-making as anomalies are detected. At the lower level, AR is performed using NN that exploits 3D data deriving from the pre-processed real-time 3D representation of the user. At the higher level, the OOBN can recognize wasteful, nonsense or dangerous behaviors, environmental discomfort, changes in behavioral patterns, and serious medical situations or events, and thus trigger specific services. Bidirectional vocal interaction with the individual is carried out through the Dialog System implemented into the Automation Hub agent based on Node-RED. The system accessibility and flexibility enables integrated tools and modules to be either fine-tuned or extended in future stages.

We also consider a number of improvements, which can be addressed as the future work of this study:

- Implementing the MS-G3D model.
- Learn the OOBN modules through data collected from a real AAL environment.
- Fully testing the whole pipeline in an end-to-end manner.

Acknowledgements

This work is partially supported by the Italian Ministry of Education, University and Research PRIN 2017 Project: "A Distributed Digital Collaboration Framework for Small and Medium-Sized Engineering and Construction Enterprises".

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