Personal Assistant Supporting Diagnosis of Livestock Poisoning

Veneta Tabakova-Komsalova
University of Plovdiv
"Paisii Hilendarski"
Plovdiv, Bulgaria
and Institute of Information and Communication Technologies, BAS,
Sofia, Bulgaria
v.komsalova@uni-plovdiv.bg

Stanimir Stoyanov
University of Plovdiv
"Paisii Hilendarski"
Plovdiv, Bulgaria
and Institute of Information and Communication Technologies, BAS,
Sofia, Bulgaria
stani@uni-plovdiv.bg

Lyubka Doukovska
Intelligent System Department Institute of Information and Communication Technologies
Bulgarian Academy of Sciences,
Sofia, Bulgaria
lyubka.doukovska@iict.bas.bg

Ivan Stoyanov
Institute of Information and Communication Technologies, BAS,
Sofia, Bulgaria
and University of Plovdiv
"Paisii Hilendarski"
Plovdiv, Bulgaria
i.stoyanov@uni-plovdiv.bg

Stoyan Cherecharov
University of Plovdiv
"Paisii Hilendarski"
Plovdiv, Bulgaria
cheresharov@uni-plovdiv.bg

***Abstract*— This paper presents a personal assistant that is able to support veterinarians in diagnosing livestock poisoning. The assistant is implemented as an intelligent agent on top of ZEMELA platform. ZEMELA provides an infrastructure for integration of the physical and virtual worlds that can be used for development of smart agriculture applications. The architecture of the assistant is also presented in the paper. Furthermore, the assistant's operation is demonstrated by a small example.**

Keywords— personal assistants, cyber-physical spaces, software platforms, virtualization of physical things, smart agriculture, agents, Prolog.

I. INTRODUCTION

In recent years, artificial intelligence (AI), enhanced by technologies such as Internet of Things (IoT), Big Data, CPSS Cyber-Physical System (CPS), is increasingly entering agriculture. The concepts of smart farming and smart agriculture are more often found in specialized AI publications. Taking into account the state of the surrounding physical world is of particular importance for the efficient operation of intelligent applications in agriculture. Moreover, with breakthroughs in science, technology and engineering, people have become increasingly involved in CPS [1]. In addition, IoT [2] has contributed significantly to the evolution of computer interconnection integrating the dynamics of physical processes with those of software and communication, providing abstractions and techniques for modeling, designing and analyzing complex integrated systems [3].

Taking into account these trends, we have developed a platform known as ZEMELA aiming to support cyber-physical applications in the field of smart agriculture. The platform provides an infrastructure for integration of the physical and virtual worlds. The agriculture-specific knowledge is presented as a network of specialized ontologies. The active components of ZEMELA are personal assistants implemented as rational autonomous, reactive, proactive BDI agents [4]. A group of specialized agents called guards accomplish the interface between the virtual and the physical worlds. The physical world is presented as an IoT Nodes Network that is able to collect up-to-date information on the "situation on the ground", i.e. sensory data from the observed open and closed agriculture areas. The network is constructed from various types interconnected devices (sensors, controllers, drones, robots).

To build a particular ZEMELA application it is necessary to integrate modules in the platform that provide a solution to a specific task (business logic). There are a huge number of tasks and challenges that can be helped by enhanced AI. A such challenge is the diagnosis of livestock poisoning. Due to their large variety and the huge number of factors that determine them, the diagnosis of poisoning is a particularly difficult task. In this article, we present a personal assistant (PA) aiming to assist veterinarians in diagnosing livestock poisoning. Our consultation shows that such an assistant would be very helpful. PA is implemented on top of the ZEMELA platform, exploiting its capabilities to support a real diagnostic process.

The paper is structured as follows: the next section provides a short overview of current projects in the domain of intelligent agriculture. The third section briefly describes the PA's architecture. The fourth section is dedicated to an example, which demonstrates the operation of PA.

II. RELATED WORKS

Recently, enormous number of projects were started aiming to develop smart agriculture platforms, environments, and applications. In Europe, the FaST project [5] supported by the European Commission's DG Agriculture and Rural Development is implemented to provide EU farmers with opportunities for agriculture, sustainability, and the environment. The platform designers are ambitious to

978-1-6654-7625-6/22/$31.00 ©2022 IEEE

establish FaST as a world leader for generating and reusing solutions for smart agriculture. Furthermore, space data gained from two another European projects (Copernicus and Galileo) can be saved and processed in the platform. Currently, the second stage of the project is under construction (started in 2021).

Within the project PlantVillage [6] supported by UN FAO, CGIAR, and other publicly funded institutions, a smart assistant known as Nuru is developed [7]. Using computer vision Nuru can help human expert by crop disease diagnostics. Furthermore, the assistant enhances the human capabilities in anomaly detection and forecasting based on ground and satellite derived data.

The Nexus platform [8] is a leading global knowledge hub for managing and sharing resources on the water, energy, and food security. It enables practitioners, researchers and policymakers to think beyond sectors to ensure access to water, energy, and food for all.

In recent years, a lot of ontologies presenting agricultural knowledge have been under development. To mention two examples. The Ontologies Community of Practice [9] is engaged in the development of ontologies for agricultural research. Their ontologies provide semantically organized terms from the agriculture domain that could facilitate the gathering, saving, and use of agronomic data, enabling easy interpretation and reuse of the data by humans and machines alike. The ontologies are based on formal categories from the Basic Formal Ontology, shared by the ontologies of the Open Biological and Biomedical Ontology Foundry family. The Livestock Ontologies group [10] cooperates research institutions and individuals to solve the problems related to presentation livestock data in a consistent manner. The group is interested in using standard dictionaries or ontologies to help classify and organize livestock data to ensure that they can be found and reused. It is a collective effort aimed at identifying common goals and outlining strategic joint activities. The group is open to anyone who is interested in researching and building dictionaries and ontologies of animal husbandry. This research group is coordinated in collaboration with the Ontologies Community of Practice, presented above.

VineSignal [11] assists growers and viticulturists to manage yield, maturity, and irrigation and also to predict grape maturity and optimal harvesting dates. The basic functions of the platform are forecasting yield for picking and vintage planning, optimizing irrigation scheduling for correct vine canopy vigour, reducing variability across the vineyard, and identification of problem areas.

III. ARCHITECTURE OF THE PERSONAL ASSISTANT

The main function of the PA is to assist veterinarians in diagnosing various types of poisoning in animals. The PA is able to assist in making preliminary and differential diagnoses. The assistant is implemented as an autonomous, reactive and proactive software component. On the one hand, it responds to user's request for assistance in diagnosing poisoning exhibiting reactive behavior. On the other hand, recognizing symptoms of a possible poisoning, PA can activate and initiate interaction with the user (exhibits proactive behavior). The PA architecture (Fig. 1) includes the basic modules presented briefly in this section.

A. Current Case Descriptor

Actually, the Current Case Descriptor (CC-Descriptor) operates as the working memory of the PA, where information about the specific case is collected. A specific case is presented as a data structure consisting of animal identification information and various symptoms known or observed by the user. The data can be obtained from various sources such as sensors mounted on animals, dialogue with the user or laboratory samples. The descriptor is used for parameterization and selection of appropriate rules from the knowledge base that are applied to preparate diagnosis of the currently affected animal.

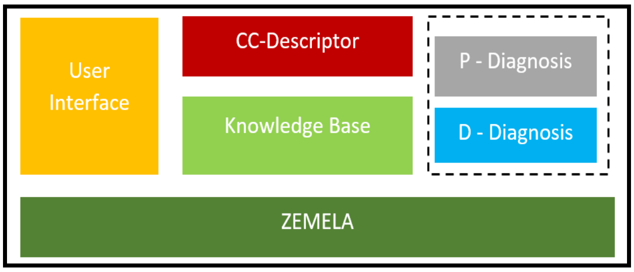

Figure 1. PA architecture - basic modules.

B. Knowledge Base

Background knowledge about poisonings is stored here. More than 40 types of poisoning are currently identified from the specialized literature. Usually, any poisoning is diagnosed by analyzing numerous and varied symptoms. In addition, poisonings can be classified on various indications. To model this diversity, we use various knowledge representations mainly semantic networks, frames, and rules. The knowledge base consists of two modules - knowledge used to prepare preliminary diagnoses and knowledge used to generate differential diagnoses.

C. Diagnosis Component

The equations are an exception to the prescribed specifications of this template. You will need to determine whether or not your equation should be typed using either the Times New Roman or the Symbol font (please no other font). To create multileveled equations, it may be necessary to treat the equation as a graphic and insert it into the text after your paper is styled The Diagnosis Component is responsible for preparation of diagnosis implementing a rule-based inference engine. The inference engine is able to operate in two modes - in the mode of preliminary diagnosis or in the mode of differential diagnosis. Each mode is supported by a separate module, which can be performed individually or jointly. In case of joint use, it is expedient to first perform the preliminary diagnosis, generating a hypothesis for possible poisoning, and then to verify this hypothesis in the module for differential diagnosis. The preliminary diagnosis module uses a forward chaining approach, in which the appropriate rules to be applied are selected based of successful unification between the conditional part of the rule and the symptoms recorded in the CC-Descriptor. The differential diagnosis module uses a backward chaining method, in which appropriate rules are those that contain the hypothesis of possible poisoning on the right (conclusion) side. The differential diagnosis may require additional (objective) information, usually provided by sensor devices mounted on animals or laboratory data.

D. User Interface

Through the user interface, the PA initiates a dialogue with the user to obtain initial information about the symptoms observed by the user (breeder or veterinarian). Usually, this information is incomplete because it is gained on the breeder's direct observations. All data received by the user through the user interface are saved in the CC-Descriptor.:

E. Platform ZEMELA

The PA is implemented on the top of the ZEMELA platform (Fig.1.); the platform provides various helpful services to the assistant. ZEMELA is implemented as a virtual-physical space, consisting of three subspaces that are presented briefly in this section.

ADK Center. The ADK Center (Agriculture Data and Knowledge Center) is a sharable distributed repository of knowledge in the agriculture field. The agriculture expertise is coded in form of semantic models presented mainly in multilevel ontologies. The data obtained from the sensor networks are aggregated and spatial-temporal information of the virtualized "things" are saved in this repository.

Analytical Subspace. This subspace is the operative component of the platform assisting agricultural operators in the managing, controlling, and coordinating all required activities and plans. The main function of this subspace is to virtualize the "things" of interest located in the physical world. To this end, a multi-model approach has been adopted. Currently, the temporal aspects of the things are modeled as a temporal network based on the Interval Temporal Logics [12]. The virtualization of the special aspects of the things is modeled by help of an ambient-oriented modelling environment known as Calculus of Context-aware Ambients [13]. The events in the analytical subspace are presented according the Event Model and are interpreted by the Event Engine [14]. The kernel of the platform are personal assistants located in the Analytical Subspace. The supported by ZEMELA applications are usually complex and difficult to use. Therefore, providing user-friendly tools (personal assistants) is highly desirable. According ZEMELA philosophy each agriculture operator may have its own personal assistant. In this context, the personal assistants operate as specialized interface between the platform and the users. The personal assistants are supported by another type of active components called operative assistants. Usually, operative assistants are server components performing various auxiliary functions and also implemented as rational BDI agents.

Guards. The Guards Subspace implements the interface between the virtual and the physical worlds. The guards are intelligent agents that serve to transform and transmit data between the two worlds. In ZEMELA, the physical world is presented as an IoT Nodes Network that is able to collect up-to-date information on the "situation on the ground", i.e. sensory data from the observed open and closed agriculture areas. In view of the fact that the climatic conditions and the terrain can be very different (especially in open areas), a wider variety of types of devices that make up the sensor network is required. The network is constructed from various types interconnected devices (sensors, controllers, drones, robots). The communication between the separate IoT Nodes is mainly implemented on a public Internet and private LoRaWAN network [15].

The platform ZEMELA is implemented by the JaCaMo framework [16].

IV. A DIAGNOSIS EXAMPLE

In this section, the operation of the PA is demonstrated by a small example. The example is running in the Win-Prolog environment [17]. A segment of the user interface is given below.

```
question attributes
   Which attributes do you know to start
with?;
   choose some of attribute_types.
group attribute_types
  gastrointestinal, nervousness,
   mouth_nostrils_eyes, cardiovascular.
question gastrointestinal
   What about gastrointestinal?;
   choose some of gastrointestinal_types.
group gastrointestinal_types
   diarrhea, vomiting, thirst, odor.
question nervousness
   What about nervousness?;
   choose some of nervousness_types.
group nervousness_types
   staggering,lying_down,unsteady_movements.
question mouth_nostrils_eyes
   What about mouth,nostrils and eyes?;
   choose some of mouth_nostrils_eyes_types.
group mouth_nostrils_eyes_types
   otitis, ulcers, redness, blisters.
question cardiovascular
   What about cardiovascular?;
   choose some of cardiovascular_types.
group cardiovascular_types
   rapid_pulse, rapid_breathing.
```

The symptoms required for diagnosis are grouped into types (attribute_types). The user can choose to enter only observed symptoms that are recorded in the CC-Descriptor. The user interface makes sure that questions about already known symptoms are not asked again. If additional information is needed, the dialogue with the user can be resumed.

Currently, the Knowledge Base specifies rules about 42 types of livestock poisoning. Two rules used to generate a hypothesis of possible fusarium poisoning (i.e., preliminary diagnosis) are given below.

```
rule fusarium1
    if the gastrointestinal are {diarrhea,
thirst, odor}
    and nervousness are {staggering,
lying_down}
    then the poisoning`s kind becomes
'FUSARIUM SPOROTRICHIELLA'.

rule fusarium2
    if  the poisoning`s kind is unknown
    and [the cardiovascular is rapid_pulse
    or  the cardiovascular is
rapid_breathing]
    and [gastrointestinal are {vomiting,
thirst, odor}
    and nervousness are {staggering,
uncertain_movements}]
```

```
   then  the  poisoning`s  kind  becomes
'FUSARIUM GRAMINEARUM'.
```

Follows a segment of the life cycle of the Diagnosis Component (inference engine). The preliminary diagnosis and differential diagnosis are running as separate processes (action run). It is also possible to first generate a hypothesis of possible poisoning and then test this hypothesis by differential diagnosis.

```
action run(Diagnosis);
   if Diagnosis is pd then
   run_pdiagnosis
   else
      if Diagnosis is dd then
         run_ddiagnosis
      else
         fail
      end if
   end if.
```

The example below demonstrates the implementation of the preliminary diagnosis (`action run_pdiagnosis`). The user interface (ask attributes) is activated, which in turn initiates a dialogue with the user to get the observed symptoms and to generate a *CC-Descriptor*.

```
action run_pdiagnosis;
   do restart
   and ask attributes
   and invoke ruleset identify
   and write(poisoning`s kind)
   and nl.
ruleset identify
   contains identity_rules;
   update ruleset by removing each selected
rule.
group identity_rules
   fusarium1, fusarium2.
   …
```

Once a CC-Descriptor has been generated, it is now possible to activate the diagnostic process (`invoke ruleset identify`). `ruleset identify` specifies the set of rules in which the appropriate rule (or rules) should be sought. Furthermore, the policy of managing the rule set (`by removing each selected rule`) is set here.

The result of the diagnosis is saved in the slot of a frame (`poisoning`s kind`), which is stored in CC-Descriptor. Further this result can be visualized and user-friendly presented (e.g. on the mobile device of the farmer or veterinarian).

V. CONCLUSION AND FUTURE WORK

This paper presents the first version of a personal assistant designed to support the diagnosis of poisoning in livestock. The architecture of the assistant is similar to that of a classic expert system enhanced with some new features. The domain knowledge is represented as rules and frames using KSL (Knowledge Specification Language) technology.

We plan to expand the assistant in several directions. First, the knowledge base will be supplemented with new knowledge about the symptoms and diagnostics of the various types of poisoning, which are very diverse. Second, the inference engine will be tested in different modes of operation. Third, a characteristic feature of intelligent agents is to take the environment into account when making decisions. Specialized laboratories and sensor devices can be located in the environment, from which data necessary for preparing diagnostics, especially for differential diagnostics, can be automatically obtained. In this way, the next version could be an IoT based personal assistant.

Along with these extensions, practical experiments are being prepared for the use of the assistant in a real diagnostic process.

ACKNOWLEDGMENT

This work is supported by the Bulgarian Ministry of Education and Science under the National Research Program “Smart crop pooduction” approved by Decision of the Ministry Council №866/26.11.2020.

We acknowledge the provided access to the e-infrastructure of the Centre for Advanced Computing and Data Processing, with the financial support by the Grant No BG05M2OP001-1.001-0003, financed by the Science and Education for Smart Growth Operational Program (2014-2020) and co-financed by the European Union through the European structural and Investment funds.

REFERENCES

[1] Wolf, W. (2009). Cyber-physical systems. Computer, volume (42), pp 88–89.

[2] Atzori, L., Iera, A., and Morabito, G. (2010). The Internet of Things: A survey, Comput. Netw., volume (54), pp 2787-2805.

[3] Shi, J., Wan, J., Yan, H., and Suo, H.(2011) A survey of cyberphysical systems. In IEEE WCSP'11, pages 1-6.

[4] Wooldridge, M. (2009). An Introduction to MultiAgent Systems, Wiley, p.488.

[5] FaST Platform, https://fastplatform.eu/

[6] PlantVillage:https://plantvillage.psu.edu/projects

[7] Nuru, https://apps.apple.com/ie/app/plantvillage-nuru/id1441395371

[8] Nexus, https://www.water-energy-food.org/.

[9] Platform for Big Data in Agriculture, https://bigdata.cgiar.org/blog-post/agricultural-ontologies-in-use-the-agronomy-ontology/.

[10] Livestock Ontologies, https://www.livestockdata.org/working-group/livestock-ontologies.

[11] Vinesignal, https://www.deepplanet.ai/vinesignal.

[12] Moszkowski, B.(1999). Compositional reasoning using Interval Temporal Logic and Tempura, Lect. Notes in Comp. Sci.,1536, Springer, 439-464.

[13] Siewe, F., Zedan, H., Cau, A.(2010). The calculus of context-aware ambients, Journal of Computer and System Sciences, volume (77), Issue 4, p. 597-620

[14] Guglev, Z., Stoyanov, S. (2018). Hybrid approach for manipulation of events in the Virtual Referent Space, International Scientific Conference “Blue Economy and Blue Development”, 1-2 June, BFU, Burgas.

[15] LoRaWAN Specification v1.1, https://lora-alliance.org/resource-hub/lorawanr-specification-v11.

[16] Boissier, O., Bordini, R., Hübner, J., Ricci, A. (2020) Multi-Agent Oriented Programming Programming. Multi-Agent Systems Using JaCaMo, The MIT Press Cambridge, Massachusetts London, England.

[17] Win-Prolog, https://www.lpa.co.uk/win.htm