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Analyzing Human Activities and Transferring Semantic Representations to Humanoid Automated Machines

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Abstract

A semantic representation framework is proposed here to conclude human activity from annotations. By utilizing elaboration of a framework, I am able to transfer tasks and skills from humanoids to automated machines. Our method allows to understand a demonstrator's behavior at a higher level of understanding through semantic representations. To achieve the required task, the demonstrators should carry out their actions in accordance with the abstracted essence of the activity derived from observations. Consequently, the motion and properties of humans and objects are combined to produce a meaningful semantic description. Moreover, three contrasting approaches were used to substantiate the semantic rules and complex kitchen activities, i.e., 1) Preparing pancakes, 2) Preparing sandwiches, and 3) setting the table, aiming determine the maintaining semantic consistency. Our study presents measurable and detailed outcomes, that show that I system can handle time constraints, a variety of execution styles by different participants when performing the same task, and various labeling strategies when executing the same task without any further training. The inferences based on the representations of one scenario, which have been obtained based upon one situation, are still effective for innovative circumstances as well, which further proves that there is no dependence between a given task and the representations derived therefrom. As a result of I experiment, I was able to successfully recognize human actions in real-time on about 87.49% of events, that was well than the accuracy from a arbitrary member diagnosing similar performances on about 77.08% of the occasions.

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1. INTRODUCTION

Hominid robots have become more capable with time as a result of skills that have been transferred to them from human observation. It is widely accepted that transferring these skills is these systems can be enhanced most effectively by [1,2]. By using semantic representations of the activities that individuals engage in, the robots will be able to get and regulate a elevated understanding of human actions by inspecting them in aspect. The robots will have the opportunity to achieve far more than they are currently capable follow them to advance beyond what they already have been able to. As humanoid robots become increasingly humanoid, the aptitude to robotically recognize human actions and respond to this behavior by producing feasible motions or actions based on user expectations will make them a revolutionary advancement.

Nevertheless, it is pertinent to point out that not all facets of a project are readily apparent; instead, some must be implied, for example, the main objectives of the prototype, which are usually provided by the researchers (as noted by the authors of [2]). A set of procedures is needed to process the data relevant to the project's objective. This will enable us to be in a position to make inferences about the project's purpose. Semantic representation is one of the most powerful tools for achieving this goal. This is because the connections between the gestures of one and the various substances around him are also useful as a way to extract the meaning of a person's way of being. This research project uses the last point as the starting point for developing a semantics based on the way people are.

1.1. A brief description of the system

The main goal is to present a framework for analyzing a person's body movements and properties of substances, which comprises three major areas of study: 1) An analysis of a person's body movements and the properties of substances, 2) a hierarchy for understanding a person's movement and attitude, and 3) a simulation of a person's movement and attitude by artificial intelligence. A diagram depicting the components of I framework, as well as their connections between each other, can be found in Figure 1.

The first module (see Figure 1) is a program that will provide assistance to automated systems to recognize and interpret images or information from a variety of media, for instance video, by recognizing different types of visual information. Extracting bits of information from the video feed will result in the analysis and preprocessing of the video, as well as segmenting the clips by their general motions: moving, not moving, and method of usage. A movement of the person's body is one that involves the body as a whole. Moreover, items and their features are used to gather two sets of information: *Object Acted On* as well as *Object In Hand*.

1.2 Setup for the experiments:

Our framework was validated by observing and recording two real and challenging tasks1: making pancakes as well as making sandwiches. As for both tasks, the experiment setup was similar (see Figure 2), where it consisted of three cameras mounted at different angles and a number of sensors.

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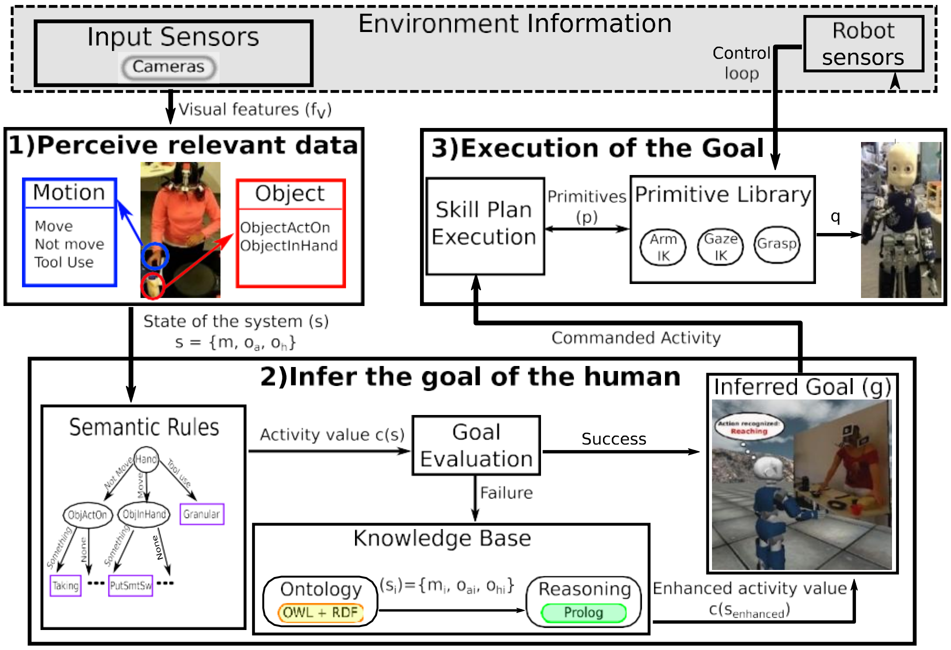

Fig. 1. In general, the system consists of three components: 1) Capturing useful data, 2) Analyzing the targets spotted, and 3) Efforts undertaken by automated machines

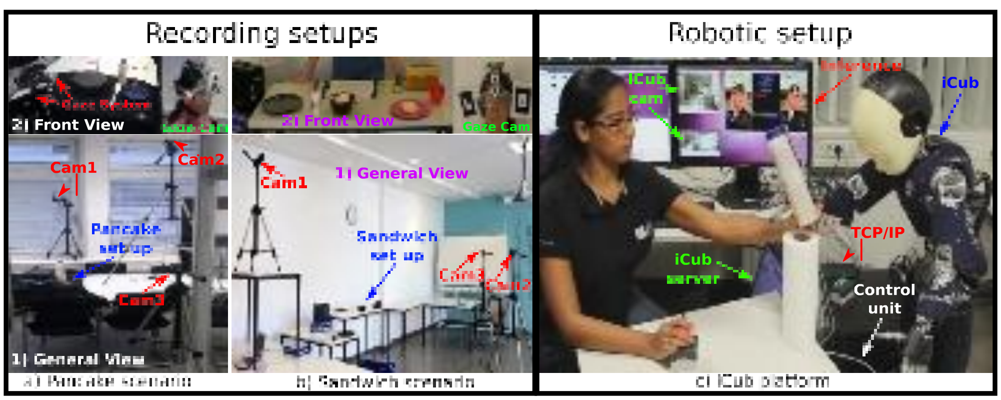

Fig. 2. The experimental apparatus consists of automated machines. A) The actual positions of the cameras during the pancake production simulation, b) The camera setup in the sandwich-preparation setup, c) The automated machines setup utilized for research substantiation in this research.

Additionally to the automated system used to evaluate the design methodology, a GNU/Linux-based workstation was utilized to validate the framework. This robot was accompanied by a control unit, a workstation, and a humanoid robot named iCub. Data were transferred from the PC to the control unit through TCP/IP on a LAN.

The Progress of this framework consists of a number of sections that are organized in a systematic manner. A brief overview of current knowledge in the field is presented in the first section; the second section describes the current state of knowledge regarding the field. During section 4, I will discuss how semantic rules were developed as well as the ontology-based representation of knowledge, which will be used analyze the data movements and substances. In unit 5, I will also discuss the method that was employed to achieve An ontology of concepts and their corresponding rules representations that I used. In the second part of the paper, I describe the process that I used in order to translate the observed humanoid activities into a robot that can perform the actions observed. The third part describes the datasets I used, and the fourth part describes their analysis. The last part concludes with I conclusions.

2. AN OVERVIEW OF CURRENT STATE-OF-THE-ART TECHNOLOGIES

In recent years, the idea of automatically segmenting, recognizing, and Observations have led to the interest of researchers from various disciplines to understand the way in which humans behave based on their observations in a variety of fields. They also identified a number of various kinds of person’s actions that are characterized on diverse stages, based on the level of intricacy of the bustle, namely gestures, actions, interactions, and group dynamics. The act of raising one's leg or stretching one's arm, for example, can be considered a gesture. As a result, the method working be reliant on the difficulty of the movement, and various trials need to be done, such as grouping the experimental movements of humans, defining the status of the object(s) for the mission, setting up multiple stages of concept, identifying important motion features, defining the standing of the object(s) for the job, and identifying the appropriate level of abstraction. In these problem domains, there is a significant problem of transferring Ideas from a particular region to another area to resolve a parallel issue. Thus, learning about patterns of human activity is still a long way from being a technology that can be easily adapted to resolve a parallel issue in a diverse area.

It can be viewed as an extension of the issue of activity recognition within the robotics domain. The main problem is to determine what the robot is supposed to do as part of its activities.

As a rule, a method of investigating the first problem is to analyze the trajectory level of human movements, that is to examine the trajectory of those movements in order to determine the information they can provide. It can also be very difficult to determine what information can be derived from the analysis of motions or similar motions in order to determine what information can be extracted from those motions. The goal of extracting expressive data from a job, for instance, is to regulate the level of abstraction is required in order to determine what information is available in order to determine what information is available in the task itself. This section will examine these problems in greater detail so that I may solve the activity recognition problem more comprehensively according to experience.

2.1. The direction of the Project

To build and develop the most accurate model of person's body movement, there has been a tendency in the robotics community to use path level representations an approach in building and developing the person's body movement. In this way, the automated machines build and develop the constraints elaborate in a job of proficiency is clearly displayed, which can be conducted over a number of trials of the same task or in most cases under a specific scenario [25,26]. Using techniques such as programming-by-demonstration [18], which are prevailing and firm methods of teaching robots new tasks based on observations are highly effective and widely used in the robotics community. Moreover, Billard et al. [18] presented a novel approach to developing the related structures of a job, based on which they recognized what to mimic by noticing the time-independent of a presentation [27] and derived a wide-ranging strategy for developing the related structures of the job.

2.2. Representation of semantic information

Several recent studies have tried to determine how much abstraction is required to excerpt expressive data from a job to figure out what the precise task could be and it is diagnosed by the researcher. Humans and objects can be analyzed on a semantic level using hierarchical approaches in order to diagnose elevated level of actions with a more composite temporal assembly on a

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semantic level. It is possible to use these approaches to analyze human or object behavior using these approaches. As well as being able to handle less training data, the system is also capable of handling less training data if it incorporates prior knowledge into its representations as well. The semantic refers to the activities within an elevated staged activity by an expert who manually incorporates this prior knowledge into the elevated staged activity. The scheme is able to adapt more easily to new situations because of these mechanisms, and by doing so it is in a position to make sense of the purpose and significance of the task it recognizes. As a matter of fact, the main sphere of activity is the primary emphasis of I study and a more wide-ranging scrutiny of these procedures can be found in the subsequent sections.

As part for their pioneering study, Kuniyoshi et al. [34] proposed an active attention control system for mapping unremitting real time events to figurative ideas that were able to be accessed by the participant. Using a moderately figurative presentation of operation approaches, Jakel et al. [35] used a (partially) symbolic representation of manipulation strategies to create the plans of automated machines as a function of pre- and post-conditions in order to generate robot plans. The frameworks, however, do not provide any reasoning about the purposes of the handler or excerpt the senses of movements from them. Alternative research that mentioned this issue was conducted by Fern et al. [36], who used a sense sub-language to develop exact-to-wide-ranging explanations of events, utilizing manual communication data, as a means of learning exact-to-wide-ranging definitions.

According to Park et al., semantics plays a vital part in the recognition of human behaviors. The semantic description of a human behavior is defined by the connection between subject, verb, and object created on the linguistic "verb argument structure," which is composed of representative–wave–goal triples. The relationships between subject, verb, and object define the behavior. As a means of generating the semantic descriptions of video events, the authors used a set of usual linguistic verbs and signs from a defined vocabulary in conjunction with visual features to create these triples. One of the advantages of natural-language descriptions is that they have a rich syntactic and semantic structure that makes it easy for them to represent rules and contexts that

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transcend domain boundaries. Though, the figure of triples must be distinct in advance as well as reliant on the intricacy of the action, many triples may be required for a exact action. There is no option of reusing these triples in innovative conditions as a result of the fact that they are not re-usable.

During the work of Yang et al. [40], they presented a scheme that could comprehend movements based on their significances, for example, separating or merging, nonetheless the fundamental basis for their method was a strong lively trailing and separation technique, that was able to spot variations in the operated object, its presence, and its topologic assembly, that is the consequence of the manipulation. In order to improve this system, it was later proposed to include a collection of strategies comprising primary accomplishment, as discussed in [41], but this was not applied in a automated machines, and if the strategy is not recognized beforehand, it will fail. There is another study that uses plan recognition to support the conclusion that human behavior is characterized by stereotypical patterns that can be categorized as preconditions and effects. [42] Kautz et al. There is, however, a problem, because in order to use these constraints in many different domains, they must be stated in advance, where is an issue.

The concept of ontology-based action recognition was proposed by Patterson et al. [9], where a prototypical uses abstract reasoning to simplify object instances based on their modules. This model poses a number of problems, including misclassification of activities in few areas, the actions are under the same category as the substance in some cases. Since they have the identical object class (clothes), action like performing laundry and getting dressed are misclassified. A practical approach has been proposed by [43] for defining the knowledge of automated machines, which composed off explanation logic information bases with data mining and (self-) comment units in order to achieve recognition using knowledge representations. In order to understand actions, the automated machines gathers knowledges and usages these experiences to develop models and aspects of action-related concepts, which is based on its awareness and accomplished system. Object–action relationships must be manually specified in this knowledge representation system.

Identifying and segmenting actions are very challenging and challenging problems to solve. In general, the computer idea and machine learning groups are attentive on explaining acknowledgement problems, but disregard segmentation problems, which are usually performed manually, as noted above. It is necessary, however, for the automated machines groups to resolve both issues in a way that is reliable, effective, and fast for automated machines to be in position to make the best decisions possible. Our current research focuses on the non-trivial tests of division, acknowledgement, and conversion of human activities to the automated systems. By combining the advantages of the techniques discussed above, I system is able to overcome the problems associated with those techniques to get considerable performance, with an accurateness exceeding 84.97% when segregating and identifying human actions in real life environments. It is in the following sections that these findings are presented.

8. CONCLUSIONS

The robotics community faces a difficult task in identifying human activities correctly, but its explanation is extremely significant since it is the initial step towards more usual human–robot interactions. The purpose of this research was to grow a method by which information about hand gesture and two object possessions are combined to excerpt the meanings of basic human actions. As a result of this information being input into the framework, the productivity is an indirect human activity that can be performed by an automated machines in real time based on the input information.

9. CONTRIBUTIONS

This study makes a number of important contributions that can be summarized in the following way.

An observation-based multilevel framework for the stretchy artificial of human activities can be proposed and implemented to facilitate the stretchy simulation of human performances.

This research I propose a humble yet operative way to obtain semantic instructions that shows the feel of human actions and its impact on the world.

A semantic rule driven reasoning engine has been proven to be effective in improving the active growth of incorporating ontologies knowledge representations.

REFERENCES

[1] S. Schaal, Is imitation learning the route to humanoid robots?, Trends Cogn. Sci. 3 (6) (1999) 233–242.

[2] C.L. Nehaniv, K. Dautenhahn (Eds.), Imitation and Social Learning in Robots, Humans and Animals: Behavioural, Social and Communicative Dimensions, Cambridge Univ. Press, Cambridge, 2007.

[3] M. Carpenter, J. Call, The question of what to imitate: inferring goals and intentions from demonstrations, in: K. Dautenhahn, C.L. Nehaniv (Eds.), Imitation and Social Learning in Robots, Humans and Animals, MIT Press, 2007.

[4] C. Nehaniv, K. Dautenhahn, The correspondence problem, in: K. Dautenhahn, C. Nehaniv (Eds.), Imitation in Animals and Artifacts, MIT Press, 2002, pp. 41–61.

[5] P.K. Turaga, R. Chellappa, V.S. Subrahmanian, O. Udrea, Machine recognition of human activities: a survey, IEEE Trans. Circuits Syst. Video Technol. 18 (11) (2008) 1473–1488.

[6] S. Park, J.K. Aggarwal, Semantic-level understanding of human actions and interactions using event hierarchy, in: Conference on Computer Vision and Pattern Recognition Workshop, 2004, CVPRW '04, 2004, p. 12.

[7] R. Poppe, A survey on vision-based human action recognition, Image Vis. Comput. 28 (6) (2010) 976–990.

[8] Q.V. Le, W.Y. Zou, S.Y. Yeung, A.Y. Ng, Learning hierarchical invariant spatio-temporal features for action recognition with independent subspace analysis, in: CVPR, IEEE, 2011, pp. 3361–3368.

[9] D.J. Patterson, D. Fox, H.A. Kautz, M. Philipose, Fine-grained activity recognition by aggregating abstract object usage, in: ISWC, IEEE Computer Society, 2005, pp. 44–51.

[10] J.K. Aggarwal, M.S. Ryoo, Human activity analysis: a review, ACM Comput. Surv. 43 (3) (2011) 16.

[11] M. Beetz, M. Tenorth, D. Jain, J. Bandouch, Towards automated models of activities of daily life, Technol. Disabil. 22 (2010) 27–40.

[12] H.S. Koppula, R. Gupta, A. Saxena,

Learning human activities and object affordances from RGB-D videos, CoRR, arXiv:1210.1207.

[13] F. Wörgötter, A. Agostini, N. Krüger, N. Shylo, B. Porr, Cognitive agents – a procedural perspective relying on the predictability of Object–Action-Complexes (OACs), Robot. Auton. Syst. 57 (4) (2009) 420–432.

[14] E.E. Aksoy, A. Abramov, J. Dörr, K. Ning, B. Dellen, F. Wörgötter, Learning the semantics of object–action relations by observation, Int. J. Robot. Res. 30 (10) (2011) 1229–1249.

[15] D. Vernon, G. Metta, G. Sandini, A survey of artificial cognitive systems: implications for the autonomous development of mental capabilities in computational agents, IEEE Trans. Evol. Comput. 11 (2) (2007) 151–180.

[16] Y. Kuniyoshi, The science of imitation – towards physically and socially grounded intelligence, in: Special Issue TR-94001, Real World Computing Project Joint Symposium, Tsukuba-shi, Ibaraki-ken, 1994, pp. 95–96.

[17] T. Inamura, T. Shibata, Geometric proto-symbol manipulation towards language-based motion pattern synthesis and recognition, in: 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2008, 2008, pp. 334–339.

[18] A. Billard, S. Calinon, R. Dillmann, S. Schaal, Survey: robot programming by demonstration, in: Handbook of Robotics, 2008.

[19] F. Hermens, S. Gielen, Posture-based or trajectory-based movement planning: a comparison of direct and indirect pointing movements, Exp. Brain Res. 159 (3) (2004) 340–348.

[20] C. Schuldt, I. Laptev, B. Caputo, Recognizing human actions: a local SVM approach, in: Proceedings of the 17th International Conference on Pattern Recognition, vol. 3, ICPR 2004, IEEE, 2004, pp. 32–36.

[21] T. Kanda, D. Glas, M. Shiomi, N. Hagita, Abstracting people 's trajectories for social robots to proactively approach customers, IEEE Trans. Robot. 25 (6) (2009) 1382–1396.

[22] H.S. Koppula, A. Saxena, Anticipating human activities using

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ISSN: 0193-4120 Page No. 436-450

object affordances for reactive robotic response, in: Robotics: Science and Systems, RSS 2013, 2013.

[23] H.S. Koppula, A. Saxena, Learning spatio-temporal structure from RGB-D videos for human activity detection and anticipation, in: ICML (3), in: JMLR Proceedings, vol. 28, JMLR.org, 2013, pp. 792–800.

[24] J. Lei, X. Ren, D. Fox, Fine-grained kitchen activity recognition using RGB-D, in: The 14th International Conference on Ubiquitous Computing, Ubicomp 2012, 2012.

[25] C. Atkeson, S. Schaal, Robot learning from demonstration, in: Proc. Int. Conf. on Machine Learning, 1997, pp. 12–20.

[26] S. Calinon, A. Billard, Incremental learning of gestures by imitation in a humanoid robot, in: ACM/IEEE International Conference on Human–Robot Interaction, ACM, 2007, pp. 255–262.

[27] A. Billard, Y. Epars, S. Calinon, G. Cheng, S. Schaal, Discovering optimal imitation strategies, Robot. Auton. Syst. 47 (2–3) (2004) 67–77.

[28] A. Ude, A. Gams, T. Asfour, J. Morimoto, Task-specific generalization of discrete and periodic dynamic movement primitives, IEEE Trans. Robot. 26 (5) (2010) 800–815.

[29] A.J. Ijspeert, J. Nakanishi, S. Schaal, Movement imitation with nonlinear dynamical systems in humanoid robots, in: ICRA, IEEE, 2002, pp. 1398–1403.

[30] S. Albrecht, K. Ramirez-Amaro, F. Ruiz-Ugalde, D. Weikersdorfer, M. Leibold, M. Ulbrich, M. Beetz, Imitating human reaching motions using physically inspired optimization principles, in: Humanoids, IEEE, 2011, pp. 602–607.

[31] D. Nyga, M. Tenorth, M. Beetz, How-models of human reaching movements in the context of everyday manipulation activities, in: ICRA, IEEE, 2011, pp. 6221–6226.

[32] D. Wolpert, Z. Ghahramani, Computational principles of movement neuroscience, Nat. Neurosci. Suppl. 3 (2000) 1212–1217.

[33] J. Bandouch, F. Engstler, M. Beetz, Accurate human motion capture using an ergonomics-based anthropometric

human model, in: Fifth International Conference on Articulated Motion and Deformable Objects, 2008.

[34] Y. Kuniyoshi, M. Inaba, H. Inoue, Learning by watching: extracting reusable task knowledge from visual observation of human performance, IEEE Trans. Robot. Autom. 10 (6) (1994) 799–822.

[35] R. Jäkel, S.R. Schmidt-Rohr, M. Lösch, R. Dillmann, Representation and constrained planning of manipulation strategies in the context of programming by demonstration, in: ICRA, IEEE, 2010, pp. 162–169.

[36] A. Fern, J.M. Siskind, R. Givan, Learning temporal, relational, force-dynamic event definitions from video, in: R. Dechter, R.S. Sutton (Eds.), AAAI/IAAI, AAAI Press/The MIT Press, 2002, pp. 159–166.

[37] W. Takano, Y. Nakamura, Humanoid robot's autonomous acquisition of proto-symbols through motion segmentation, in: 6th IEEE–RAS International Conference on Humanoid Robots, IEEE, 2006, pp. 425–431.

[38] M. Wächter, S. Schulz, T. Asfour, E. Aksoy, F. Wörgötter, R. Dillmann, Action sequence reproduction based on automatic segmentation and object–action complexes, in: IEEE/RAS International Conference on Humanoid Robots (Humanoids), 2013.

[39] D. Gehrig, P. Krauthausen, L. Rybok, H. Kuehne, U.D. Hanebeck, T. Schultz, R. Stiefelhagen, Combined intention, activity, and motion recognition for a humanoid household robot, in: IROS, IEEE, 2011, pp. 4819–4825.

[40] Y. Yang, C. Fermüller, Y. Aloimonos, Detection of manipulation action consequences (MAC), in: CVPR, IEEE, 2013, pp. 2563–2570.

[41] A. Guha, Y. Yang, C. Fermuuller, Y. Aloimonos, Minimalist plans for interpreting manipulation actions, in: 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, 2013, pp. 5908–5914.

[42] H.A. Kautz, H.A. Kautz, R.N. Pelavin, J.D. Tenenberg, M. Kaufmann, A formal theory of plan recognition and its implementation, in: Reasoning About Plans, Morgan Kaufmann, 1991, pp. 69–

125.

[43] M. Tenorth, M. Beetz, KnowRob: a knowledge processing infrastructure for cognition-enabled robots, Int. J. Robot. Res. 32 (5) (2013) 566–590.

[44] K. Ramirez-Amaro, E.-S. Kim, J. Kim, B.-T. Zhang, M. Beetz, G. Cheng, Enhancing human action recognition through spatio-temporal feature learning and semantic rules, in: 13th IEEE–RAS International Conference on Humanoid Robots, 2013.

[45] G.R. Bradski, A. Kaehler, Learning OpenCV – Computer Vision with the OpenCV Library: Software That Sees, O'Reilly, 2008.

[46] K. Ramirez-Amaro, M. Beetz, G. Cheng, Automatic segmentation and recognition of human activities from observation based on semantic reasoning, in: IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2014, IEEE, 2014.

[47] T.M. Mitchell, Machine Learning, McGraw–Hill, 1997.

[48] R. Quinlan, C4.5: Programs for Machine Learning, Morgan Kaufmann Publishers, San Mateo, CA, 1993.

[49] S.J. Russell, P. Norving, Artificial Intelligence: A Modern Approach, Prentice–Hall, Upper Saddle River, New Jersey, 1995.

[50] J. Wielemaker, Z. Huang, L. van der Meij, SWI-Prolog and the web, Theory Pract. Log. Program. 8 (3) (2008) 363–392.

[51] V. Vassiliadis, J. Wielemaker, C. Mungall, Processing OWL2 ontologies using Thea: an application of logic programming, in: R. Hoekstra, P.F. Patel- Schneider (Eds.), OWLED, in: CEUR Workshop Proceedings, vol. 529, CEUR-WS.org, 2008.

[52] G. Metta, G. Sandini, D. Vernon, L. Natale, F. Nori, The iCub humanoid robot: an open platform for research in embodied cognition, in: PerMIS: Performance Metrics for Intelligent Systems Workshop, 2008, pp. 19–21.

[53] E. Dean-León, V. Parra-Vega, A. Espinosa-Romero, J. Fierro, Dynamical image-based PID uncalibrated visual servoing with fixed camera for tracking of planar robots with a heuristical predictor, in: 2nd IEEE International

Conference on Industrial Informatics, 2004, INDIN'04, IEEE, 2004, pp. 339–345.

[54] U. Pattacini, Modular Cartesian controllers for humanoid robots: design and implementation on the iCub, Ph.D. thesis, 2010.

[55] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, I.H. Witten, The WEKA data mining software: an update, ACM SIGKDD Explor. Newsl. 11 (1) (2009) 10–18.

[56] K. Ramirez-Amaro, M. Beetz, G. Cheng, Extracting semantic rules from human observations, in: ICRA'13 Workshop: Semantics, Identification and Control of Robot–Human–Environment Interaction, 2013 IEEE International Conference on Robotics and Automation, IEEE, 2013.

[57] K. Ramirez-Amaro, M. Beetz, G. Cheng, Transferring skills to humanoid robots by extracting semantic representations from observations of human activities

[58] K. Ramirez-Amaro, M. Beetz, G. Cheng, Understanding the intention of human activities through semantic perception: observation, understanding and execution on a humanoid robot, Adv. Robot. 29 (5) (2015) 345–362.