Knowledge Model Quantitative Evaluation for Adaptive World Modeling

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***Abstract*—World modeling can provide environment information to applications for decision support and situation assessment. In a semantic world model like the Object-Oriented World Model (OOWM), knowledge about an application domain is modeled a priori. In practice, however, world modeling systems have to deal with an open world, where unforeseen real-world entities can occur during operations. To enable open-world modeling for the OOWM, an approach to adaptive knowledge management is presented. This approach proposes an information-theoretic model evaluation based on the Minimum Description Length principle.**

***Keywords*-model evaluation; object-oriented world modeling; information-theoretic measures; minimum description length**

I. Introduction

Within applications designed for situation assessment or situational awareness support, situations and their constituent parts have to be represented accordingly. A proven solution for representing the objects constituting situations of interest is the use of a world modeling system like the OOWM [1], which has been successfully applied to tasks like assessing situations in the maritime domain [2] or providing a memory structure and information hub in the domain of autonomous systems [3]. The OOWM consists of two parts, a dynamic World Model, acting as an architecture for associating, fusing and storing observations provided by heterogeneous sensors, and a static Background Knowledge, representing the entities (objects, situations, etc.) of the domain of interest as concept classes. This knowledge model enables the classification of observed real-world entities based on their attribute values, and furthermore allows to derive additional, yet unobserved entity information. The concept classes in Background Knowledge are modeled a priori and represent the entities that are considered to be of interest for the tasks at hand, e.g., in situation assessment. In consequence, only a limited and closed world is modeled a priori.

During operations, however, the OOMW may observe real-world entities that have not been modeled in Background Knowledge and thus cannot be classified according to the predefined concept classes. In order to cope with such circumstances and to allow for open world modeling, we propose an adaptive approach for managing the information represented in the OOWM Background Knowledge. This adaptive approach comprises methods for evaluating the quality of the knowledge model with regard to its ability for explaining the currently observed world as well as methods for identifying points of necessary change to Background Knowledge. Within the OOWM, information processing is handled by probabilistic methods based on the Bayesian paradigm. All real-world observations as well as all attributes of concept classes are thereby represented as probability distributions. An evaluation of model quality thus requires to compare the probability distributions resulting from environment observations to those distributions used for characterizing the concept classes in Background Knowledge. The evaluation has to quantify how well observed entities are represented, or explained, by the a priori modeled concepts. In this contribution, we take an approach based on the Minimum Description Length information principle and propose a framework for rating the quality of a knowledge model based on information-theoretic measures. Related work concerns unsupervised approaches to classification and concept acquisition like Numerical Taxonomy and Conceptual Clustering. In Numerical Taxonomy ([4], applied e.g. in [5]), groups of entities are formed and sorted into taxonomic structures based on the attributes of considered entities. Conceptual clustering [6] extends this approach to a classification based on probabilistic concepts, for which explicit definitions are acquired from observations. A survey of proposed approaches to Conceptual Clustering is given in [7], while [8] examines a unified treatment of discrete and continuous attributes for Conceptual Clustering. Recent approaches to visual category discovery [9] detect and discover unknown concepts on images by classifiers.

This contribution is structured as follows. Section II provides an overview of the OOWM approach. Section III introduces the adaptive information management approach to world modeling. In Section IV, the proposed framework for quantitatively evaluating the model quality of Background Knowledge is presented. Section V gives a proof of concept and presents evaluation results for an example domain.

II. Object-Oriented World Modeling

The OOWM [1], [3] is a probabilistic data and information fusion framework which allows to represent a real-world

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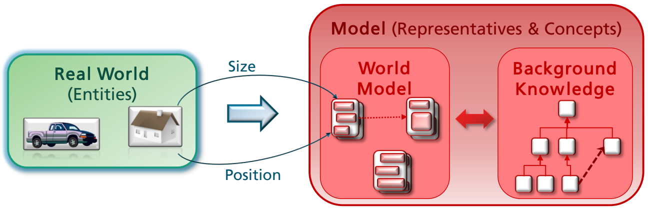

Figure 1. Overview of Object-Oriented World Modeling. Observed real-world entities are represented as representatives in the World Model, based on a priori defined concept classes in Background Knowledge.

domain based on observation data and a priori knowledge. Intended as a general framework for world modeling, the OOWM is able to integrate observations from heterogeneous sensing systems and can be employed in different application domains. It is designed to serve as a persistent memory structure and information hub, and can provide higher level processing modules with consistent and integrated information representing the current or historic state of an observed environment. It thus is well suited to serve as a basis for structured situation assessment services, decision support applications and other cognitive processing.

The OOWM consists of two components, depicted in Figure 1. Observations of entities, like the position, size or color of real-world objects, can be provided to the OOWM by various sensing systems and get stored in the dynamic modeling part denoted as World Model. Observed entities are represented as information objects called representatives which constitute sets of observed attributes $\mathcal{A}_R := \{A_1, A_2, \dots, A_n\}, n \in \mathbb{N}$. Each attribute observation $A_i \in \mathcal{A}_R$ is represented by a probability distribution $p_{A_i}(a)$, describing the degree of belief (*DoB*) in the observed value. Using DoB distributions to describe observations allows to treat arising uncertainties, e.g. related to the observation process, in a systematic manner. The OOWM approach assumes stochastic independence for attribute distributions, allowing to represent the joint distribution for a representative as the product $p(\mathcal{A}_R) = p(A_1, A_2, \dots, A_n) = \prod_{i=1,\dots,n} p_{A_i}(a)$ of its univariate attribute distributions. As attribute distributions, discrete probability distributions

$$p^d_A : \mathcal{S}_A \mapsto [0,1] \ \text{ with } \ |\mathcal{S}_A| \leq \infty \,, \ \sum_{a \in \mathcal{S}_A} p^d_A(a) = 1 \,,$$

are used to represent nominally, ordinally and absolutely scaled attributes and continuous probability distributions

$$p^c_A : \mathcal{D}_A \subseteq \mathbb{R} \mapsto [0, \infty) \quad \text{with} \quad \int_{\mathcal{D}_A} p^c_A(a)\, \mathrm{d}a = 1$$

are used to represent interval scaled and ratio scaled attributes. For continuous distributions, especially Gaussian and Gaussian mixture distributions are employed.

The second component of the OOWM is the Background Knowledge, which represents knowledge about an application domain as a priori defined model. This model is the result of a conceptualization process, in which each entity relevant to the application domain is modeled as an object-oriented concept class and represented in Background Knowledge. A concept class C in Background Knowledge is characterized by its set $\mathcal{A}_C := \{A_1, A_2, \dots, A_m\}$ of attributes, representing the entity attributes, and a number of necessary class relations for the modeled entity (e.g., part_of relations). In analogy to the description of representatives, attributes are represented by probability distributions $p_{A_c}(a)$, and the joint probability distribution of a concept is given as the product $p(\mathcal{A}_C) = \prod_{i=1,\dots,m} p_{A_i}(a)$ of its attribute distributions, again assuming stochastic independence.

Within the OOWM, probabilistic information processing following the Bayesian methodology is employed. When an observation is received, it is either associated to an existing representative, based on its location, or a new representative is created. Existing representatives get updated by new observations, either by extending the set $\mathcal{A}_R$ of observed attributes by an additional attribute observation A_{n+1}, or by updating the DoB distribution of one attribute $A_i \in \mathcal{A}_R$ that has already been observed. For updating and fusing DoB distributions, a Kalman filter and its extension are employed. In addition, a probabilistic aging mechanism degrades the degree of belief in attribute observations over time, if they are not reconfirmed.

The connection between the dynamic World Model and the a priori Background Knowledge is established by a probabilistic classification mechanism, which associates an representative R to a concept C by a conditional probability distribution $p(C|R)$, based on the set of observed attributes $\mathcal{A}_R$ as well as on the set of modeled concept attributes $\mathcal{A}_C$. Besides classification, the Background Knowledge can be employed to derive further information on observed entities, e.g. information on attributes that have not yet been observed or unobservable higher-level information concerning the function or meaning of entities.

In the OOWM, all information processing is applied on the basis of a discrete model of time. In consequence, all information, including the attribute sets $\mathcal{A}_R$ of representatives and their DoB distribution $p_{A_i}(a)$, must be represented in relation to a discrete point of time. For simplicity, discrete time indices are omitted in this contribution wherever possible. For each point of time, the information on attributes and relations gets persisted, thus allowing to access information about domain states for all past points of time. Such historic information is valuable for adjusting and improving the OOWM system during operations. More details on the OOWM approach can be found in [3].

III. Adaptive Knowledge Management for Open-World Modeling

In OOWM Background Knowledge, information considered as relevant for an application domain is modeled a priori by human experts. Background Knowledge thus is only able to represent a closed domain. However, a world modeling system used to support tasks like situation assessment in complex domains is likely to encountered entities that have not been considered during initial modeling. In order to handle such situations, an approach for adjusting the knowledge model to an open world is required. For the OOWM, open-world modeling corresponds to adaptively managing the concept classes in Background Knowledge used to represent observed real-world entities.

Adaptive knowledge management for world modeling constitutes of several separate sub-tasks. First, an approach for quantitatively evaluating the quality of the knowledge model is needed. In the OOWM, model quality has to reflect how well the Background Knowledge is suited for representing the so far observed real-world entities. Based on this quantitative rating, a management process can be used to continuously evaluate the quality of Background Knowledge for representing sensor observations. If a degradation in quality is detected, the process has to identify where and how the knowledge model has to be extended or adjusted to ensure its quality. This means that those representatives in the World Model have to be identified which are only insufficiently represented by the current concept classes. Then, model improvement procedures can be applied, like generating new concept classes based on the identified representatives or extending existing concepts, as well as rating different alternatives to improving overall model quality.

A central part of the adaptive knowledge management approach within object-oriented world modeling is the problem of how to evaluate the quality of a knowledge model. The primary purpose of the OOWM Background Knowledge is to allow a classification of observed entities, i.e., to map representatives to modeled concept classes, and, on top of that, to derive additional information about these entities. Thus, the correspondence of a priori modeled knowledge to observed information is a main factor for rating model quality in object-oriented world modeling. Further aspects of model evaluation can be the usefulness of the knowledge model for answering queries or performing reasoning as well as the formal correctness of the model according to general modeling principles, for example derived from formal ontology like in OntoClean [10].

IV. Quantitative Model Evaluation

The main focus for model evaluation in this contribution is set to the classification performance of Background Knowledge. The evaluation thus focuses on rating the correspondence of observed entities with modeled concept classes and on rating the complexity of the employed knowledge model.

The parameters determining the quality of Background Knowledge in this approach are the set of representatives $\mathcal{R}$, including all observed attributes $\mathcal{A}_R$, as well as the set of concept classes $\mathcal{C}$ in Background Knowledge. In addition, the association $p(C|R)$ of each representative $R \in \mathcal{R}$ to a concept $C \in \mathcal{C}$ impacts model quality. For a measure $Q(\cdot)$ rating the overall quality of OOWM knowledge, all these parameters have to be taken into account.

A. MDL-based Model Evaluation

For implementing such a measure, an approach based on the principle of Minimum Description Length (*MDL*, described in detail e.g. in [11]) was chosen. In MDL-based approaches to inductive inference, the aim is to select models which allow to represent observed data with a description of minimal encoding length. For that purpose, regularities are extracted from observed data and formalized into models, which then can be used to describe the observed data in a compressed way: by only representing deviations of observed data from the model and the model itself. In crude MDL as presented by [11], a two-part term is used to rate the description length L of a model M for data D according to $L = L(D|M) + L(M)$. The term $L(D|M)$ represents the length of a description needed to represent the data D based the model M, and $L(M)$ represents the length of the description for the model itself.

Following this general idea of crude MDL, we propose

$$Q(\mathcal{R}, \mathcal{C}) \;=\; L(\mathcal{R}|\mathcal{C}) \;+\; L(\mathcal{C}) \tag{1}$$

to be used as a measure for rating the quality of Background Knowledge, based on the current observation information in the World Model. In addition to the term $L(\mathcal{R}|\mathcal{C})$, which rates to correspondence of observed data to modeled information, the term $L(\mathcal{C})$ is used to rate the complexity of the model. Model complexity can be seen as a constraint, as used in many kinds of classification problems, to be applied during model adaptation, preventing the model from overfitting the observation data, and thus maintaining the ability of the model to generalize.

B. Rating Model Complexity

To rate the model complexity, a measure for the description length of Background Knowledge has to be designed. The proposed measure is designed according to the following assumptions. The overall model complexity $L(\mathcal{C})$ of the concept set $\mathcal{C}$ in Background Knowledge is to be evaluated based on the complexity of each concept $L(C)$, $C \in \mathcal{C}$. The more complex a single concept is rated, the more complex the overall model shall be rated *(a)*. A single concept shall be rated the more complex, the more specific it is. Concept specificity is defined based on its attributes. A concept is more specific the more attributes $A_c \in \mathcal{A}_C$ it is described with and the more specific the description of each attribute is *(b)*. Due to the assumption of stochastic independence for concept attributes, each attribute can be rated separately. In consequence, for rating model complexity according to the presented assumptions, the cumulative measure

$$L(\mathcal{C}) \overset{(a)}{:=} \sum_{C\in\mathcal{C}} L(C) \overset{(b)}{=} \sum_{C\in\mathcal{C}} \sum_{A_c\in\mathcal{A}_C} L(A_c) \qquad (2)$$

$$\overset{(c)}{=} \sum_{C\in\mathcal{C}} \sum_{A_c\in\mathcal{A}_C} L\left(p_{A_c}(a)\right)$$

is employed, where DoB distributions $p_{A_c}(a)$ are used to rate the specificity A_c of attributes *(c)*. The specificity of probability distributions can be evaluated based on the concentration of its features to only certain values of the support of the distribution. As such a measure, being invariant to value dispersion, Shannon entropy $H(\cdot)$ is employed for rating attribute specificity in an information-theoretic manner. For a discrete attribute A^d with DoB distribution $p^d_A(a)$, the Shannon entropy is $H(A^d) = -\sum_{a\in S_A} p^d_A \cdot \log(p^d_A(a))$. This entropy is greater the less concentrated a distribution is. Assuming a limited set $\mathcal{S}_A$ of attribute values, i.e., a limited support for the DoB distribution $p^d_A(a)$, we can use the entropy $H(A^d)$ for rating the specificity of a discrete attribute according to the measure

$$L_1(A^d) := \log(|\mathcal{S}_A|) - H\big(A^d\big) \; . \qquad (3)$$

This measure explicitly accounts for the support of an attribute. An alternative measure normalizing the attribute complexity to the interval $[0,1]$ is given by

$$L_2(A^d) := 1 - \frac{H(A^d)}{\log(|\mathcal{S}_A|)} \, . \qquad (4)$$

C. Handling of Continuous Attributes

For continuous DoB distributions $p^c_A(a)$, a continuous variant of entropy, the differential entropy $h(A^c) := -\int_{\mathcal{D}_A} p^c_A(a)\cdot\log(p^c_A(a))\,\mathrm{d}a$, can be employed to rate attribute specificity. Differential entropy, however, as a measure of entropy for continuous probability distributions, differs in some important properties from Shannon entropy. If, for example, a continuous distribution is quantized into bins, the Shannon entropy of this quantization changes with bin size and its value differs from differential entropy by the logarithm of the bin size, as described for example in [12]. For rating the specificity of continuous attributes, differential entropy possesses two further undesired properties. First, it is scale-dependent, as for any $a \in \mathbb{R}$, $h(a \cdot A^c_c) = h(A^c_c) + \log(|a|)$. This property is undesired when rating ratio-scaled attributes, which can be given in different units of measurement. And second, differential entropy can take negative values, due to the fact that continuous probability distributions can have values greater than 1. This fact makes it difficult to calculate concept complexity as the sum of complexity values for its attributes. To overcome these limitations, we propose to use a quantization of DoB distributions for rating continuous attributes by specifying a least discernible quantum (*LDQ*) for each attribute. This LDQ, as presented in [13] for the classification of OOWM representatives, was introduced as a general approach in information theory in [14]. The LDQ of an attribute characterizes the level of precision at which attribute values are to be distinguished. Yet it is lower-bound by the precision of the methods used for measuring the attribute, it should be seen as a design parameter dependent on the OOWM application domain rather than a technical limitation.

For calculating the quantized entropy $H(A^c, \Delta_A)$ of a continuous attribute A^c with DoB distribution $p^c_A(a)$ and the LDQ Δ_A, the domain of A^c is discretized into bins of size Δ_A, and each bin is assigned the portion of the probability mass of $p^c_A(a)$ located within its extent (this corresponds to building a histogram with equal bin size Δ_A). Thus, a discrete attribute A^Δ with discrete distribution $p^d_{A^\Delta}(a)$ results. Based on this LDQ quantization, the Shannon entropy of the discrete attribute is employed to specify the quantized entropy $H(A^c, \Delta_A) := H(A^\Delta)$. For rating attribute complexity by the presented measures $L_1(\cdot)$ and $L_2(\cdot)$, the number of bins resulting from the discretization of the attribute domain $\mathcal{D}_A$ is needed, representing the cardinality of the discretized domain $|D_{A_\Delta}|$. To calculate this number, limits for the attribute domain have to be given.

D. Rating of Description Quality

The second term needed for evaluating the quality of the OOWM knowledge in the proposed MDL-based approach (1) is the correspondence $L(\mathcal{R}|\mathcal{C})$ of so far observed information and a priori modeled information. Here it is assumed that the better observed information is matched by modeled information, the less description is necessary for representing the observed information - thus, the lower the respective description length. If a representative matches a concept class in Background Knowledge, it can be described through this concept. If not, it has to be described by the best matching concept (e.g., an abstract concept) and additionally, by the differences of its attributes to the concept attributes, thus resulting in a more complex description.

Our approach to rating the description quality of Background Knowledge is based on the correspondence $L(\mathcal{R}|\mathcal{C}) := \sum_{R\in\mathcal{R}} \sum_{C\in\mathcal{C}} p(C|R) L(R|C)$ between all representatives R currently stored in the World Model and the concepts C in Background Knowledge to which these representatives have been associated with a non-zero classification probability $p(C|R)$. When hard classification decisions are made, the correspondence is rated as

$$L^{'}(\mathcal{R}|\mathcal{C}) := \sum_{R\in\mathcal{R}} L\big(R \mid C = \bar{C}(R)\big) \, , \qquad (5)$$

where $\bar{C}(R)$ denotes the concept that a given representative R has been associated with. The individual correspondence rating $L(R|C)$, needed in both alternatives, is calculated based on the attributes of a representative R according to

$$L(R|C) = \sum_{A_r\in\mathcal{A}_R} w_{A_{c_r}} \cdot L(A_r|A_{c_r}) \, , \qquad (6)$$

where $A_{c_r} = \bar{A}(A_r) \in \mathcal{A}_C$ is the concept attribute corresponding to the observed attribute A_r, and $w_{A_{c_r}}$ denotes a weighting factor that can differ for individual attributes.

To rate the attribute correspondence $L(A_r|A_{c_r})$, a measure reflecting the description quality of A_{c_r} for A_r must be applied. The main idea behind description quality is about how much additional information is necessary for describing an observed attribute when using the concept attribute to represent the observed attribute. A deterministic observation value, for example, could be regarded as well represented if it lies within the bulk mass of a concept DoB distribution. If it does not, its distance, e.g. to the mean, could be used to quantify the amount of additional description needed. For stochastic attribute observations represented as DoB distributions, the attribute correspondence $L(A_r|A_{c_r})$ must constitute a function for comparing probability distributions. When using a LDQ quantization of attributes as presented above, only discrete distributions $p^d_A(a)$ have to compared. As information-theoretic measures, the Kullback Leibler divergence, also known as relative entropy $D_{KL}(A_r||A_{c_r}) = \sum_{a \in A_r} p^d_{A_r}(a) \cdot \log(p^d_{A_r}(a) \,/\, p^d_{A_c}(a))$ as well as the cross entropy $H(A_r, A_{c_r})$, described e.g. in [12], can be employed for the comparison. As further measures, cross correlation and a discrete scaled overlap measure $L_o(A_r, A_{c_r}) = \sum_{a \in A_r} l_o(a) \; \leq 1$ with

$$l_o(a) := \begin{cases} 0\,, & \text{if } \tilde{p}^d_{A_r}(a) \leq p^d_{A_c}(a) \\ \left|\, p^d_{A_r}(a) - p^d_{A_c}(a) \,\right|, & \text{otherwise} \end{cases} \tag{7}$$

can be employed. For comparing probability values in $l_o(\cdot)$, a scaled variant $\tilde{p}^d_{A_r}$ of $p^d_{A_r}$ is used.

The ideal measure should assign a value close to zero to each observed attribute, whose DoB distribution is largely located within the bulk probability mass of the corresponding concept attribute, and the more apart the probability masses lie, the higher the assigned value should be. If an observed attribute has no corresponding attribute in the considered concept A_{c_r}, a uniform distribution over the attribute domain is used for calculating $L(A_r|A_{c_r})$.

V. Evaluation and Proof of Concept

For demonstrating and evaluating the presented quality measures, a world modeling example based on a kitchen scenario is used. In our kitchen example, fruits are considered as the entities of interest and, for evaluation purposes, concept classes for apples and coconuts have been explicitly modeled. Each entity is thereby characterized by one exemplary continuous attribute, here specifying a length in cm, and one exemplary discrete attribute, specifying e.g. a color as a nominal value (white, blue, green, yellow, orange, red, or brown). Table I depicts the exemplary Background Knowledge for this kitchen scenario, which contains the additional compound concept AppleCoconut for representing entities that are either Apple or Coconut.

Entity	*Length in cm*	*Color (w, b, g, y, o, r, br)*
Apple	$\mathcal{N}_1 = \mathcal{N}(7,1)$	r: 0.5, g: 0.3, y: 0.2
Coconut	$\mathcal{N}_2 = \mathcal{N}(18,4)$	br: 1
AppleCoconut	$0.5(\mathcal{N}_1 + \mathcal{N}_2)$	r: 0.25, g: 0.15, y: 0.1, br: 0.5

Table I
Background Knowledge for an example kitchen scenario

First, concept complexity is evaluated based on the measures for attribute specificity $L(A_c)$. Table II shows the Shannon Entropy H and complexity measures L_1 and L_2 (3), (4) for some attributes. As can be seen, the specificity of the color attribute for the combined concept AppleCoconut, being a super concept to Apple and Coconut, is less than its value for Apple color. For the continuous length attribute, $H(\cdot)$ takes a negative value if evaluated on Apple. If discretized with an LDQ of 1 cm, assuming a bounded domain of 50 cm, feasible values can be reached for $H(\cdot)$ and both specificity measures. Figure 2 depicts the quantization of the length attribute for Apple and AppleCoconut. The concept complexity results as the sum of attribute specificities, e.g., $L_1(\text{Apple}) = 3.55$ and $L_1(\text{AppleCoconut}) = 1.86$.

A_c	$H(A_c)$	$L_1(A_c)$	$L_2(A_c)$
Color (Apple)	1.030	1.050	0.505
Color (AppleCoconut)	1.208	0.738	0.379
Length (Apple)	−3.187	–	–
Length$^{\Delta=0.01}$ (Apple)	1.459	2.454	0.627
Length$^{\Delta=0.01}$ (AppleCoconut)	2.783	1.129	0.289

Table II
Entropy and specificity for discrete and continuous attributes from the kitchen scenario

Second, description quality as a measure of correspondence $L(A_r|A_{c_r})$ of observed attributes to modeled attributes is evaluated. Figure 3 depicts the description quality of a concept attribute (a) used for describing an observed attribute (b). In (c) to (f), the description quality (ordinate) when shifting the mean (abscissa) of this observed attribute from left to right in its domain is rated by different measures. Relative entropy in (c) and discrete overlap (7) in (f) show promising results as they assign low ratings to observation distributions that coincide with the concept distribution, and high ratings to not corresponding distributions. Since the discrete overlap measure is bounded by 1, it can be used as an absolute measure for rating attribute description quality.

Finally, for rating the overall model quality, the proposed measures have to be combined. For evaluation purposes, a scenario over 5 discrete time steps t is supposed. As concepts only Apple is contained in the example Background Knowledge. The scenario proceeds as follows: at the first time step $t = 1$, no entity is observed. At $t = 2$, a yellow-

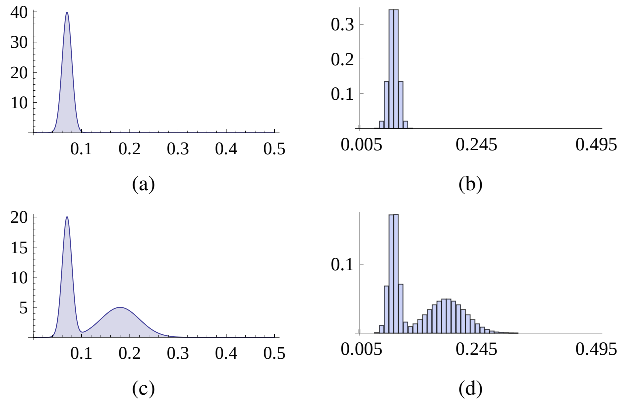

Figure 2. Exemplary DoB distribution for the length (in m) of Apple as (a) continuous attribute and (b) discretized attribute with a LDQ of 1cm. Length DoBs for the combined concept class AppleCoconut are shown as (c) continuous attribute and (d) discretized attribute.

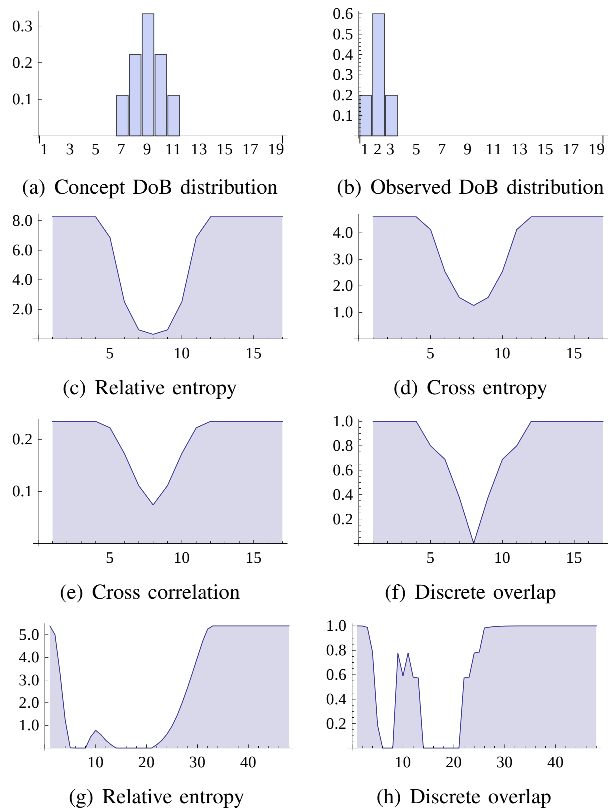

Figure 3. Evaluation of description quality for attribute distributions. Depicted are the values for several attribute correspondence measures $L(A_r|A_{c_r})$ for the concept attribute (a) and the observation attribute (b). For evaluation, the mean of the observation attribute is shifted from 2 to 18, and the diagrams (c) to (f) depict the description quality for each shift, rated by different measures. In the same manner, (g) to (h) depict the description quality of the discretized length attribute for the concept AppleCoconut.

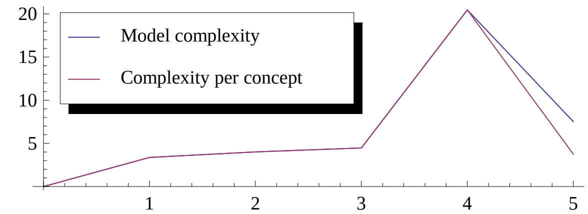

Figure 4. Evolution of model quality, measured as combined description length of the knowledge model and all observations, for an exemplary scenario over 5 discrete steps of time.

green apple with length $\mathcal{N}(6, 0.5)$ is observed, and a red apple with length $\mathcal{N}(6, 0.2)$ at $t = 3$. Then, at $t = 4$, a brown coconut is encountered with length $\mathcal{N}(18, 0.5)$. Finally, at $t = 5$, no new entity is observed, but the concept Coconut is added to the example Background Knowledge. Figure 4 displays the evolution of model quality for the described scenario. The model quality $Q(\mathcal{R}, \mathcal{C})$ is rated as description length (1), based on (2) with (3), a hard association (5), equal weights in (6) and a scaled variant of relative entropy. Lower values for $Q(\mathcal{R}, \mathcal{C})$ represent better quality. As can be seen in Figure 4, the overall model quality in the first three time steps $t = 1, 2, 3$ is dominated by (and equal to at $t = 1$) the model complexity $L(\mathcal{C})$ of the defined Apple concept. At $t = 2$ and $t = 3$, the observations of the two apples decrease model quality, as expected, by adding each a small amount of additional description. At $t = 4$, however, the description length increases by a leap, because the observed coconut is not well described by the example Background Knowledge containing only the concept Apple. This situation can be countered by adding an additional concept to Background Knowledge. For evaluation purposes, the predefined concept Coconut was added to the example Background Knowledge at $t = 5$, re-improving model quality. For a real application, no predefined concepts can be assumed. When model quality decreases, an adaptive modeling system will have to acquire new concept definitions on the fly, based on those observations being not well represented by the Background Knowledge in place at that point of time. How to acquire such definitions is yet subject to future research.

VI. Conclusion

In this contribution, an approach to adaptive knowledge management for object-oriented world modeling was presented. A model evaluation framework allowing to quantitatively evaluate the quality of a knowledge model with respect to observed information was proposed as main part. Based on this evaluation, it is possible adjust and extend a priori model information adaptively to an open world.

Future work will concern the evaluation of hierarchical knowledge models as well as a further elaboration of model adaptation, especially considering the generation of new concept classes based on insufficiently represented observations.

REFERENCES

[1] I. Gheta, M. Heizmann, and J. Beyerer, "Object Oriented Environment Model for Autonomous Systems," in *Proceedings of the second Skövde Workshop on Information Fusion Topics*, H. Boström, R. Johansson, and J. van Laere, Eds. Skövde Studies in Informatics, 2008, pp. 9–12.

[2] Y. Fischer and J. Beyerer, "Acceptance of Automatic Situation Assessment in Surveillance Systems," in *Proceedings of the IEEE Conference on Cognitive Methods in Situation Awareness and Decision Support*, 2012, pp. 324–331.

[3] A. Belkin, A. Kuwertz, Y. Fischer, and J. Beyerer, "World Modeling for Autonomous Systems," in *Innovative Information Systems Modelling Techniques*, C. Kalloniatis, Ed. InTech, 2012.

[4] R. R. Sokal, "Numerical Taxonomy," *Scientific American*, vol. 215, no. 6, pp. 106 — 116, 1966.

[5] K. Pedersen, J. K. Allen, and F. Mistree, "Numerical Taxonomy: A Systematic Approach to Identifying Potential Product Platforms," in *Proceedings on the International Conference on Engineering Design (ICED'01)*. WDK Publications, 2001, pp. 515–522.

[6] D. H. Fisher, "Knowledge Acquisition Via Incremental Conceptual Clustering," *Machine Learning*, vol. 2, no. 2, pp. 139–172, Sep. 1987.

[7] W. Iba and P. Langley, "Unsupervised Learning of Probabilistic Concept Hierarchies," in *Machine Learning and Its Applications, Advanced Lectures*. Springer-Verlag, 2001, pp. 39–70.

[8] R. B. Rebouças and J. J. V. Furtado, "Formation of Probabilistic Concepts through Observations Containing Discrete and Continuous Attributes," in *The Florida AI Research Society Conference*, 2004.

[9] Y. J. Lee and K. Grauman, "Object-Graphs for Context-Aware Visual Category Discovery," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 2, pp. 346–358, 2012.

[10] N. Guarino and C. A. Welty, "Evaluating ontological decisions with OntoClean," *Communications of the ACM*, vol. 45, no. 2, pp. 61–65, 2002.

[11] P. D. Grünwald, *The Minimum Description Length Principle*, ser. MIT Press Books. The MIT Press, 2007, vol. 1.

[12] T. M. Cover and J. A. Thomas, *Elements of Information Theory*. New York, NY, USA: Wiley-Interscience, 1991.

[13] A. Belkin and J. Beyerer, "Information Entropy and Structural Metrics Based Estimation of Situations as a Basis for Situation Awareness and Decision Support," in *Proceedings of the IEEE Conference on Cognitive Methods in Situation Awareness and Decision Support*, New Orleans, USA, Mar. 2012.

[14] J. Oswald, *Diacritical Analysis of Systems: a Treatise on Information Theory*, ser. Ellis Horwood series in electrical and electronic engineering. E. Horwood, 1991.