1. Informações sobre a candidatura
1. Application form information

Tipo de Bolsa
Type of Fellowship

Bolsa de Pós-Doutoramento
Post-doctoral Grant

Domínio Científico Principal
Main Scientific Domain

Engenharia Eletrotécnica, Electrónica e Informática
Engenharia Eletrotécnica, Electrónica e Informática

Local de realização da Bolsa
Location of fellowship activities

Mista
Both in Portugal and Abroad

4. Programa de trabalhos
4. Working programme

4.1. Título do programa de trabalhos
4.1. Title of the working programme

Open-ended learning in robotic systems

Domínio Científico
Scientific Domain

Robótica

Descreva sucintamente a forma como considera que a(s) instituição(ões) de acolhimento e o(s) orientador(es) são adequados à execução do plano de trabalhos:
Briefly describe how you consider that host(s) institution(s) and the supervisor(s) are suitable for the implementation of the working plan:

This proposal addresses problems that require expertise in the fields of Robotics and Computer Vision / Machine Learning. In particular, the goal aims at better adjusting computer vision algorithms to the requirements of service robots, focusing on their deployment in real world scenarios. Professors António Moreira and Vítor Santos both have extensive experience in robotics, as is displayed by their cv´s. The Centre for Robotics and Intelligent Systems (C-ROB) at INESC-TEC currently has three ongoing EU-projects in which open-ended learning algorithms are directly applicable. Close cooperation with these projects will foster the development of the work plan. Professor Angel D. Sappa is a senior research scientist at the Computer Vision Center of the Autonomous University of Barcelona. His expertise in the field of Computer Vision will be a great contribution to the development of the works. The Computer Vision Center is, as the name says, a research institute entirely devoted to the field of Computer Vision. The supervision of Prof. Sappa will be given weekly through skype talks, but in addition several two week stays at the Computer Vision Center in Barcelona could be scheduled. Each supervisor is more than capable of providing valuable input in their respective fields. The combination of both fields will certainly provide an opportunity to bring these two fields together, and contribute to the future deployment of service robots. It should be mentioned has previously worked with both Prof. Santos and Prof. Sappa, which somehow shows their capability of collaborating from a distance. That collaboration has resulted in several co-authored research publications as well as in joint research project proposals and co-organized research activities.

Data de início do programa de trabalhos / **Work programme starting date**	**Duração (meses)** / **Duration (month)**
01-01-2016	60

Data de início pretendida para a bolsa / **Fellowship starting date**	**Duração (meses)** / **Duration (month)**
01-01-2016	60

Permanência no estrangeiro com início em / **Periods of permanence abroad**	**Duração (meses)** / **Duration (month)**

4.2. Sumário

4.2. Abstract

Despite considerable progress in recent years, learning / recognition algorithms are not yet ready to be implemented in service robots [Guo2014]. The reason is that most of classical learning approaches are designed to be trained offline, using a training set of labeled examples. Given the unstructured nature of the environments in which service robots operate (e.g. houses, offices), it is difficult to establish which examples should be included in the training set. If they are to be deployed in real world scenarios, service robots require a set of perceptual capabilities that enable them to operate efficiently. Moreover, rather than being static, those capabilities must be enhanced over time, as robots will have opportunities to learn further from novel experiences. We refer to these learning systems as open-ended learning systems, and to the context in which they are required, i.e., settings where the number of categories to be learned is unbounded, as open-ended domains.

Our goal is to investigate how object category learning algorithms can be extended in order to operate efficiently in open-ended domains. This will have direct impact in service robotics, bringing the future deployment of service robots one step closer, but could also play a key role in the enhancement of industrial applications, rendering the processes of reconfiguration unnecessary. We will also propose evaluation methodologies designed to assess the performance of open-ended learning algorithms.

4.3. Estado da Arte
4.3. State of the art

An open-ended domain refers to an experiment or application where the system should learn continuously new object categories, i.e., the number of object categories is not known beforehand [Kirsten2012][Mitchell2015]. Nowadays, there are documented systems which can efficiently support the interface between a supervisor agent (typically a human instructor) and the autonomous system, enabling actions such as teaching a new category or correcting a previously known category (see [Rouanet2013] for an evaluation of the impact of Human Robot Interfaces in VOR, see [Oliveira2014] for an example). Thus, robotic systems often have opportunities to operate some kind of knowledge refinement throughout their lifetime.

Bag of Words (BOW) representations are suitable for open-ended domains because they propose a simplified representation of the features extracted from an object view, through the grouping of those features into clusters (e.g. K-means, Mean-shift, etc) [Perronnin2008]. These clusters are commonly referred to as words, and the set of words used to describe the object is called the dictionary or visual codebook. Because clustering is done offline, the representativeness of this training set, i.e., how well the features in the set describe the features that the system will find when running online, becomes critical to the clustering process and, consequently, to the performance of the system [Patricia2014] [Kuznetsova2015]. This is most noticeable in open-ended domains, because the categories to be learned are not known a priori and may yield feature patterns which were not included in the codebook training set.

Consequently, one of the critical challenges with the BOW model is to find an optimal set of words for the problem at hand, i.e., how to define the codebook. Taking this into account, some authors have addressed this by proposing to bond together the codebook construction with the training of object category models. The rationale is that, if the clustering is disconnected from the classification, the representation will not capture the aspects of the data that are most useful for the classification problem. In [Yang2008], a framework is proposed that unifies the clustering and classification problems using a Discriminative Cluster Refinement approach. Results show this is especially useful when the size of the training set is limited. A generative model based on latent aspects for explaining images at feature descriptors level is proposed in [Larlus2009]. In this case, the codebook is a built-in component of the model learned simultaneously with other parameters. In [Zhang2009], an optimization method is proposed that takes into account the category information as additional information for the construction of the codebook. These methodologies have interesting recognition performances, which shows that the construction of the codebook is a critical component for the recognition performance. However, it is not straightforward how these approaches could be applied to open-ended domains.

An alternative approach to the problem is to start with a very large offline codebook and then refine it: in [Perronnin2008], object categories are represented by bipartite histograms. These histograms contain the category signature in a universal codebook as well as in codebooks specifically adapted to each of the categories. However, all codebooks are constructed offline during a training stage. In addition, since the adaptive codebooks are derived from the universal one, this approach has the constraint that the number of words in the adaptive codebooks must be the same as in the universal codebook, which in turn, must be defined a priori.

There are some works which propose online updating of BOW codebooks: in [Nicosevici2012], the codebook update mechanism is limited to the merging of clusters or creation of new ones. That means that a complete restructuring of the codebook (if the data suggest that is the best way to proceed) is not possible using this approach; in [Mairal2010], an online optimization algorithm based on stochastic approximations is presented which can be applied to codebook learning; in [Skretting2010], a recursive Least Squares learning algorithm is proposed to continuously update the codebook, in order to avoid the (many times unfeasible) batch processing of large training sets. While [Nicosevici2012] focuses on scene recognition for SLAM applications, the works in [Mairal2010] and [Skretting2010] only approach the mechanisms for updating the codebooks online, without evaluating the impact of the performance of object recognition. None of those works targets concurrent learning, nor the problem of open-ended learning of object categories.

4.4. Objectivos
4.4. Objectives

This work will focus on the development of tools designed to extend the Bag-of-Words (BOW) model so that it can be applied to open-ended scenarios. Initially, we will focus in the BOW model because results have shown that it can yield very interesting results in object recognition applications. More advanced techniques such as Fisher vectors and deep learning will be studied later.

Classical machine learning approaches are not well suited for coping with open-ended settings, because they: a) require a complete training set to train; b) execute training offline; c) are not prepared for unbalanced number of examples in the categories: d) are not incremental, in most cases. This suggests the development of a new class of learning algorithms, which should: a) learn incrementally; b) learn opportunistically, i.e. learn from whatever examples are available; c) handle unbalanced datasets.

On the other hand, classical evaluation techniques such as leave-one-out or k-fold cross validation are not well suited to assess the performance of open-ended learning systems, because they rely on training / test sets and in offline training phases. Thus, this work will also focus on the development of novel evaluation methodologies for open-ended learning algorithms.

We plan to achieve the following objectives:

1. Develop novel open-ended learning algorithms, and show how they outperform classical approaches.

2. Develop new evaluation methodologies designed to assess the performance of open-ended learning algorithms, and compare proposed approaches with others under this evaluation framework.

3. Study the extension of existing learning approaches to open-ended domains.

4. Design and develop a robotic system that will be capable of learning continuously novel object categories, using feedback from humans and crowdsorcing strategies.

5. Test learning systems operating for large periods of time. The prototype will be setup on a public access hallway, so that everyone can interact with the system. The system will be capable of learning new objects and activities. This experience will provide a valuable assessment of how open-ended systems could operate and which problems they will encounter.

6. Transfer open-ended learning automatic recognition systems to industrial applications, by contacting Portuguese SMEs. Here, the tradition of synergistic cooperation with the industry accredited to INESC-TEC will be critical.

The accomplishment of these objectives will produce conference and journal papers, as well as an open-ended learning system demonstrator as described bellow. In addition, we expect that the supervision of student working on this topic will output several Msc (and possibly one PhD) thesis.

4.5. Descrição detalhada
4.5. Detailed description

In order to be deployed, service robots need to robustly recognize the objects present in the environment in which they operate. This is a challenging task because of the very large number of objects present in household environments and, moreover, due to the infinite variety in appearance of those objects. Given this, the appropriate strategy to solve the problem is to make robots capable of learning on site, rather than to exhaustively program them before deployment. This calls for online and incremental learning capabilities, in the sense that the representation of known object models should be enhanced (e.g., augmented, corrected or replaced) over time [Kuznetsova2015]. Furthermore, the need to learn previously unknown object categories implies that the learning system is open-ended, as in a problem of multinomial classification in which the number of classes is continuously increasing. Thus, open-ended learning comprises both online and incremental learning, but additionally it requires the ability to learn additional categories regularly

[Chauhan2011], [Kirstein2012], [Mitchell2015].

Note that the specific requirements of open-ended domains rule out many of the state of the art machine learning techniques used in Visual Object Recognition (VOR). One reason is that computer based VOR approaches are typically structured in two phases, learning and recognition, which are often secluded from each other. For example, despite their recent popularity, deep artificial neural networks, are incremental by nature (every new training observation can be used for updating the weights in the network), but not open-ended, since the inclusion of novel categories enforces a restructuring in the topology of the network. In humans there is no evidence of a partition between learning and recognition. On the contrary, several studies suggest that VOR learning is a protracted process that starts in early childhood and follows through to adolescence [Juttner2006]. Experiments in children from 6 to 11 years old, designed to assess their object recognition skills, suggested a maturation process of complex visual perceptual abilities, possibly related to the development of the cerebral processes involved in object recognition [Bova2007]. Given that children progressively learn more object categories, it appears there is a concurrent development of both the object recognition skills as well as of the underlying visual capabilities used in that recognition.

We argue that offline training is one of the critical factors impeding the performance of recognition systems. The construction of a training set requires comprehensive knowledge about the classes that are to be recognized as well as their discriminative characteristics. In the typical deployment scenarios of service robots, one cannot expect to have such complete and detailed knowledge beforehand. One simple example: a domestic robot serving a coffee to a human. In order to do so, the robot must grasp a mug from the kitchen. Classical training would require the training set to contain examples of mugs. One cannot expect that a training set is exhaustive enough to list all possible appearances of the object mug. Even if that is possible, further extending this strategy to all kitchenware or household objects is certainly not feasible. This is just a small example. Nonetheless, it typifies one of the critical challenges still ahead of the Computer Vision and Robotics communities: rather than learning offline, robots should have the capability to learn continuously over time. In the example above, the robot should have first collected an experience of the mug, in order to conceptualize this object category. This procedure is to be done after deployment in the working location. This opens up an additional research question which is how to design such systems to be opportunistic learners, in the sense that they must collect experiences whenever possible, in a variety of ways, both in supervised and unsupervised fashion: robots can interpellate humans, request for online assistance using crowdsourcing mechanisms, asking for names of specified objects, or they can unsupervisedly gather new views of known objects. If they are to be deployed in real world scenarios, service robots require a set of perceptual capabilities that will enable them to recognize objects, persons, locations, human performed activities, etc. Moreover, these capabilities should be flexible enough to be driven forward by novel experiences, to be collected after deployment. From a research standpoint we are interested in open-ended learning algorithms as well as in the methodologies used in their evaluation.

Open-ended learning algorithms:
Our initial focus for learning algorithms will be on the Bag of Words (BOW) model. We propose to research novel methodologies that support online learning of BOW dictionaries. It is expected that, using these techniques, the recognition performance will increase in particular in open-ended applications. Later, we plan to investigate how other learning approaches (e.g., SVM, Deep Learning) can be expanded to support open-ended learning.

Evaluation of Open-ended algorithms:
To evaluate open-ended learning systems, one must assess the performance of the system continuously over the multiple stages of the learning process. Moreover, the performance of an open-ended learning system should not limited to the accuracy with which the system recognizes the learned objects. We will propose new evaluation methodologies, which will address the following questions when considering an open-ended system:
How much does it learn? A measure of the number object categories the system is capable of learning (see [Chauhan2011] for an early study on this topic); How well does it learn? A measure of how good is the system in recognizing the learned objects. Standard measures for offline learning such as accuracy, precision and recall are well suited for this; How fast does it learn? A measure of how long it takes or how much effort is involved in learning a given category.

The current proposal is organized in the following tasks:

Task 1. Literature Review (continuous)
Throughout the project, there will be a continuous review and update of the state of the art. We will study learning algorithms (BOW, SVN, deep learning neural networks, Fischer vectors, etc.) and see if/how they can be adapted to open-ended learning domains.

Task 2. Evaluation Methodologies (12 m)
We plan to start from the work of [Chaunhan2011] and search for other performance metrics which could be useful for evaluating open-ended learning algorithms, and also plan to propose novel evaluation metrics. Existing approaches will be evaluated using these methods.

Task 3. Online learning of BOW Dictionaries (18 m)
Development of mathematical tools / algorithms for continuous update of dictionaries. Gaussian Mixture Models, for example, are interesting models, and there are some promising works that discuss how they can be updated online. Study of when is the best moment to conduct an update of the dictionaries: in a BOW algorithm, a change of dictionary is a core change, that will affect the basis of the representations of object categories. It can sometimes imply a (momentary) setback to the performance of the learning.

Task 4. Open-ended learning with other approaches (18 m)
Extension of other learning approaches to open-ended domains. Study of the memory requirements and memory explosion problems. Assess how feasible and scalable are the current learning and recognition systems under open-ended settings.

Task 5. Design and development of a robotic system for testing open-ended learning algorithms (8 Months)
We plan to construct a robotic prototype that will be capable of interacting and learning from non-expert users over long periods of time. The system will be prepared to interact with humans (e.g., detecting pointing, menus for labeling categories), which can teach new concepts to the system. In addition, the system will use crowdsorcing mechanisms to require remote assistance for labeling unknown objects of activities.

Task 6. Evaluation and tests (3+2+2+2+3 m)
The work will consist of iterative development cycles, where feedback from evaluations and test is continuously gathered to improve the approaches. We plan to carry out “open-ended” experiments. For one month, we will have, in the hallway of a public building, a robotic system which is capable of learning about objects and human activities.

Task 7. Industrial applications (3+3+3 m)
In industrial applications, often there are systems which must be reconfigured whenever there is a change in the list of parts to be handled. An open-ended learning system could be used to avoid these costly processes of manual reconfiguration. We will apply open-ended learning to scenarios defined by EU projects with industrial focus (e.g. http://stamina-robot.eu/) that are currently ongoing at INESC TEC.

The execution of these tasks will lead to the following milestones (papers submitted to major conferences in the fields of computer vision or robotics (e.g., IROS, ICRA, CVPR, ICCV, etc) or to top journals (T. on Image Processing, T. on Pattern Analysis and Machine Intelligence, T. On Robotics):

M1 - Survey paper: challenges ahead in the extension of existing learning methodologies to open-ended domains.
M2 - Paper proposing novel methodologies for evaluating open-ended learning.
M3 - Functioning Robot prototype.
M4 - Paper proposing novel methodologies for open-ended learning using the BOW model.
M5 - Paper comparing proposed methodologies with other approaches.
M6 - Paper discussing the expansion of a classical learning approach to open-ended domains.
M7 - Public presentation of a robotic prototype which learns in an open-ended fashion.

We have submitted a manuscript to IROS2015 on this topic [Oliveira2015].

4.6. Anexos
4.6. Attachments

Nome Name	Tamanho Size
timeline.pdf	**27,96Kb**

4.7. Referências
4.7. References

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5. Condições de acolhimento
5. Host conditions

5.1. Instituicao de Acolhimento 1
5.1. Host Institution

Unidade de I&D
Unidade de I&D

INESC TEC – INESC Tecnologia e Ciência

5.1. Instituicao de Acolhimento 2
5.1. Host Institution

Autonomous University Barcelona (UAB)

Departamento
Department

Computer Vision Center

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Espanha

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5.2 Orientadores
5.2 Supervisors

Nome Completo do orientador
Supervisor's full name

António Paulo Gomes Mendes Moreira

Instituição
Institution

Faculdade de Engenharia Universidade do Porto (FEUP), INESC TEC

Summary of Activities for FCT Scholarship – Final Report

Miguel Armando Riem de Oliveira, researcher, INESC TEC, INESC Technology and Science, Porto, Portugal.

Supervisor: António Paulo Moreira, Associate Professor, Faculty of Engineering University of Porto, Portugal.

Co-supervisors: Vitor Manuel Ferreira dos Santos, Associate Professor, Department of Mechanical Engineering, University of Aveiro, Professor Angel Domingo Sappa, Senior Researcher, Facultad de Ingeniería en Electricidad y Computación, Escuela Superior Politécnica del Litoral, Equator and Computer Vision Center, Autonomous University of Barcelona, Spain.

Title of work: Open-ended learning in robotic systems
FCT scholarship reference: SFRH/BPD/109651/2015
This report refers to the full period of the scholarship, start date: 01/10/2015, Finish date: 31/08/2017

Summary of Activities

Throughout this two year period the scholarship holder has published in total 7 journal papers, and 4 papers in international conference proceedings or book chapters. Apart from this publication record, the scholarship holder has also participated in other academic activities such has supervision of students, organization of events, chair of international conferences and editor of journals. Finally, the scholarship holder has also actively participated in the the writing of two project proposals for the 2017 FCT R&D project call. Furthermore, the scholarship holder has actively pursued industrial partnerships that may be able to support future projects.

Supervisions

Cosupervisor of Rodrigo António Nunes Salgueiro, Bin-picking Condicionado por Mapeamentos 3D e Referências CAD, Integrated M.Sc. in Mechanical Engineering, University of Aveiro.

Organization of Events

The scholarship holder participated in the organization of the following:

1. Special session on Autonomous Driving and Driving Assistance Systems, at the ROBOT2015 conference, November 2015 (see [1] and [2]).
2. co-organizer of the special session on Advanced Visual Perception in Robotics, ICIAR2016, International Conference on Image Processing and Analysis, July 2016, Póvoa do Varzim, Portugal (see [3]).
3. Special session on Autonomous Driving and Driving Assistance Systems, at the ROBOT2017 conference, November 2017 (see [4]).

Editor and Reviewer of International Journals and Conferences

The scholarship holder has acted as an invited guest editor for the Journal of Robotics and Autonomous Systems, in particular for the Special Issue on Autonomous Driving and Driving Assistance Systems from 2015 [5] (special issue only published in 2017) and 2017 [6] (to be published in the future). In addition, the scholarship holder has also reviewed several works submitted to international conferences and journals, namely.: Robotics and Autonomous systems, Neurocomputing, IEEE/RSJ 2008 International Conference on Intelligent RObots and Systems (IROS); International Conference on Image Analysis and Recognition (ICIAR).

Academic acts

The scholarship holder was a member of the juri as examiner in the following academic acts: Jorge Soares de Almeida, Seguimento Ativo de Agentes Dinâmicos Multivariados usando Informação Vetorial, Ph.D. in Mechanical Engineering, University of Aveiro, June 2016; Ana Carolina Matos, Ana Carolina Matos, Desenvolvimento de um Sistema de Visão Estéreo com Grande Linha de Base para a Identificação de Peões e Outros Alvos em Estrada, M.Sc. In Mechanical Engineering, University of Aveiro, June 2016; Prasanna

1 https://paginas.fe.up.pt/~robot2015/index.php/special-sessions

2 http://lars.mec.ua.pt/robot2015addas/

3 https://www.aimiconf.org/iciar16/specialsession-01.php , note that this special session was later fused with another and in the final program (https://www.aimiconf.org/iciar16/programdetails.php) it appears under the name Visual Perception in Robotics and RGB-D Cameras.

4 https://lars.mec.ua.pt/robot2017addas/

5 http://www.sciencedirect.com/science/article/pii/S0921889017300568

6 https://www.journals.elsevier.com/robotics-and-autonomous-systems/call-for-papers/call-for-papers-of-special-issue-on-autonomous-driving-and-d

Koumar Routray, Entertainment Robot for Catching a Flying Ball, M.Sc. In Industrial Automation Engineering, University of Aveiro, July 2016.

Published Results

The following list of publications contains metrics for each publication. These informations were retrieved, for indexed publications, from the Journal Citation Report from Thompson Reuters (JCR) or from the Scimago Journal & Country Rank (SJR), from the respective websites. The information displayed is for the closest year to the year of the publication in question. In all cases, the year used in the computation of the metric is signaled. Note that the following list contains only publications not mentioned in the first year report.

Journal Papers

Oliveira, M.; Santos, V.; Sappa, A. D.; Dias, P., and Moreira, A. P., Incremental scenario representations for autonomous driving using geometric polygonal primitives, Robotics and Autonomous Systems (2016), ISSN: 0921-8890, DOI: 10.1016/j.robot.2016.05.011, 2016.
IF 1.618, 10 de 25 em Robotics (Q2), 58 de 130 em Computer Science and Artificial Intelligence (Q2), (JCR2015)
SJR 1.377, 74 de 1142 em Computer Science Applications (Q1), 38 de 598 em Control and Systems Eng. (Q1), (SJR2015)

Oliveira, M.; Seabra Lopes, L.; Lim, G. H.; Kasaei, S. H.; Tomé, A. M., and Chauhan, A., 3D object perception and perceptual learning in the RACE project, Robotics and Autonomous Systems 75, Part B (2016) pp. 614–626, ISSN: 0921-8890, DOI: 10.1016/j.robot.2015.09.019, 2016.
IF 1.618, 10 de 25 em Robotics (Q2), 58 de 130 em Computer Science and Artificial Intelligence (Q2), (JCR2015)
SJR 1.377, 74 de 1142 em Computer Science Applications (Q1), 38 de 598 em Control and Systems Eng. (Q1), (SJR2015)

Sappa, A. D.; Carvajal, J. A.; Aguilera, C. A.; Oliveira, M.; Romero, D., and Vintimilla, B. X., Wavelet-Based Visible and Infrared Image Fusion: A Comparative Study, Sensors 16.6 (2016) p. 861, ISSN: 1424-8220, DOI: 10.3390/s16060861, 2016.
IF 2.033, 12 de 56 em Instruments & Instrumentation (Q3), (JCR2015)
SJR 0.546, 215 de 1536 em Electrical and Electronic Eng. (Q2), (SJR2015)

Kasaei, S.; Tomé, A. M.; Lopes, L. S., and Oliveira, M., GOOD: A Global Orthographic Object Descriptor for 3D Object Recognition and Manipulation, Pattern Recognition Letters (2016) , ISSN: 0167-8655, DOI: 10.1016/j.patrec.2016.07.006, 2016.
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Aveiro, 26 of September 2017

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