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MARIE SKŁODOWSKA-CURIE ACTIONS

Individual Fellowships (IF)
Call: H2020-MSCA-IF-2015

PART B

"ProDeepCAD"

This proposal is to be evaluated as:

Standard GF

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0 LIST OF PARTICIPANTS

Participants	Legal Entity Short Name	Academic	Non-academic	Country	Dept. / Division / Laboratory	Supervisor	Role of Partner Organisation
Beneficiary							
- NAME							
Partner Organisation							
- NAME							

Data for non-academic beneficiaries

Name	Location of research premises (city / country)	Type of R&D activities	No. of fulltime employees	No. of employees in R&D	Website	Annual turnover (approx. in Euro)	Enterprise status (Yes/No)	SME status (Yes/No)

Note that:

- Any inter-relationship between different participating institutions or individuals (e.g. family ties, shared premises or facilities, joint ownership, financial interest, overlapping staff or directors, etc.) must be declared and justified in this part of the proposal;
- The information in the table for non-academic beneficiaries must be based on current data, not projections;
- The data provided relating to the capacity of the participating institutions will be subject to verification during the Grant Agreement preparation phase.

That will be the abstract of the proposal

1 EXCELLENCE

1.1 Quality, innovative aspects and credibility of the research

1.1.1 Introduction

In Europe, prostate cancer is reported to be the most frequently diagnosed cancer of men and thus one of the leading cause of death of cancer[1]. Currently, addressing this issue is a major public debate, in which the implementation of appropriate screening methods and subsequent treatments is key. In this regard, the European Randomised Study of Screening for Prostate Cancer (ERSPC) is conducted to investigate the potential benefits of a population-based screening[2]. The screening consists of a Prostate-Specific Antigen (PSA) test and depending of the PSA level measured, an additional "blind" biopsy is carried out. Despite that mortality significantly decreases, the employed screening strategy suffers of a high rate of over-diagnosis and over-treatment[3], due to the fact that prostate cancers grow either slowly or fast. The slow-growing tumours account for up to 85 % of all cancers and stay confined to the prostate gland, while the fast-growing tumours rapidly develop and metastasise to other organs, significantly affecting the morbidity and mortality rate. Furthermore, prostate cancer is more likely to develop in specific regions of the prostate: around 70-80 % of prostate cancers originate in the Peripheral Zone (PZ), whereas 10-20 % in the Central Gland (CG), but are more aggressive and more likely to invade other organs. **Thus, additionally to cancer detection, the screening methods need to estimate the cancer aggressiveness to allow clinicians to act accordingly.**

In addition, the investigators of the ERSPC have concluded that the use of *"multi-parametric Magnetic Resonance Imaging (MRI) and the development of new markers are the hope for the future"*. That is why, Computer-Aided Diagnosis (CAD) systems, revolved around mono- and multi-parametric MRI, are currently developed by the medical imaging community, and have been recently reviewed by Lemaître *et al.*[4]. The developed CAD systems are designed under the same architecture as depicted in Fig. 1. The available MRI modalities during prostate exam are T_2-Weighted (T_2-W)-MRI, Diffusion Weighted (DW)-MRI, Dynamic Contrast-Enhanced (DCE)-MRI, and Magnetic Resonance Spectroscopy Imaging (MRSI). Additionally, Apparent Diffusion Coefficient (ADC) map is based on the computation of a coefficient derived from multiple DW-MRI acquisition. **Currently, no CAD system has been developed using all the available modalities and thus discarding their potential discriminating power to diagnose prostate cancer.** The closest attempts have used three of these modalities (i.e., T_2-W-MRI, DW-MRI, DCE-MRI) and have discarded MRSI[5,6]. This latter, however, has been shown to be extremely helpful to grade cancer aggressiveness particularly in the CG[7], which is the most challenging zone in terms of cancer detection. **Furthermore, the current researches solely focus on the delineation of prostate cancers rather than on the cancer aggressiveness assessment.**

Therefore, the aim of this project is to design a CAD system able to both detect and assess prostate cancers using all currently available multi-parametric MRI modalities. To achieve this goal, we will revisit the different stages of the CAD framework. First, we will insure to work with the most consistent data, enhancing them using different types of pre-processing. Subsequently, we will segment the prostate zones using multi-parametric MRI images

These methodologies will be extensively presented and argued in Sect. 1.1.2.

[1] J. Ferlay et al. "Cancer incidence and mortality patterns in Europe: Estimates for 40 countries in 2012". In: *Eur. J. of Cancer* 49.6 (2013), pp. 1374 –1403.

[2] F. H. Schroder et al. "Screening and prostate cancer mortality: results of the European Randomised Study of Screening for Prostate Cancer (ERSPC) at 13 years of follow-up". In: *The Lancet* 384.9959 (2015), pp. 2027 –2035.

[3] C. Delpierre et al. "Life expectancy estimates as a key factor in over-treatment: the case of prostate cancer". In: *Cancer Epidemiol* 37.4 (2013), pp. 462 –468.

[4] G. Lemaître et al. "Computer-Aided Detection and Diagnosis for Prostate Cancer based on mono and multi-parametric MRI: A review". In: *Comp. in Bio. and Med.* 60 (2015), pp. 8 –31.

[5] G. Litjens et al. "Computer-aided detection of prostate cancer in MRI". in: *Med. Imag., IEEE Trans. on* 33.5 (2014), pp. 1083 –1092.

[6] S. Viswanath et al. "Enhanced multi-protocol analysis via intelligent supervised embedding (EMPrAvISE): detecting prostate cancer on multi-parametric MRI". in: *Proc. SPIE 7963, Med. Imag. 2011: Computer-Aided Diagnosis*. 2011.

[7] E. K. Vos et al. "Multiparametric Magnetic Resonance Imaging for Discriminating Low-Grade From High-Grade Prostate Cancer." In: *Inves. Rad.* (2015).

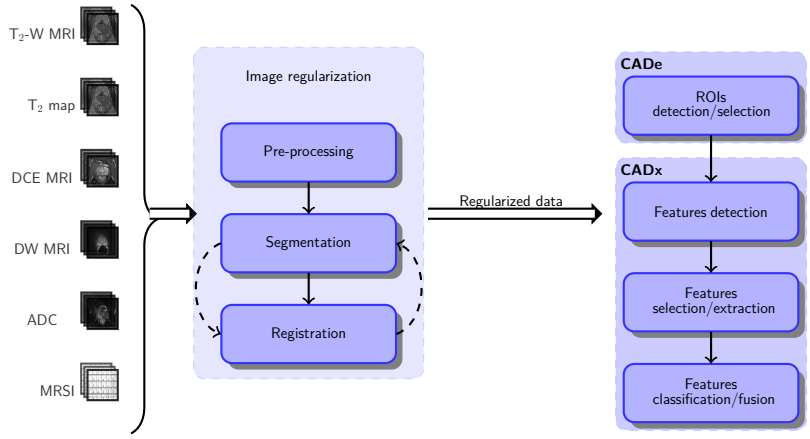

Figure 1: Common CAD framework based on MRI images used to detect prostate cancer.

1.1.2 Research methodologies

Data acquisition The unavailability of public dataset in medical imaging is a major drawback. Currently, no multi-parametric MRI prostate data are publicly available, implying that no fair comparisons can be drawn between the different developed CAD systems. Recently, Lemaître *et al.* launch a beta web-platform [8] intended for reporting the evaluation of CAD systems. A multi-parametric MRI dataset is made available, containing 60 patients and the following modalities: T_2-W-MRI, DW-MRI, DCE-MRI, and MRSI. Furthermore, the data are acquired from both 1.5 T and 3.0 T MRI scanner. Multiple ground-truths (i.e., prostate zones, cancer lesions) are compiled by experienced radiologists and additional biopsy tests. However, the web-platform need to be finalised before to be fully available. **Consequently, we will finalise the dataset and release it publicly through our web-platform.**

Pre-processing MRI images are corrupted by different phenomena: (i) bias field, (ii) noise, and (iii) inter-patient variations. In this regard, particular attention to correct each of these drawbacks will be addressed.

MRI images are affected by the inhomogeneity of the MRI field called bias field, resulting in a smooth variation of the intensities across each image. Although bias correction methods are commonly used to enhance brain MRI images[9], only one CAD system for prostate has reported to use such pre-processing[10]. The same authors have empirically evaluated the state-of-the-art methods[11] concluding that N3 algorithm[12] yields to better classification performance than other methods[13,14]. Recently, Lin *et al.*[15] have proposed a method combining the N3 algorithm with the FCM algorithm[16] which outperforms the original methods, in terms of breast segmentation. **Therefore, we will compare these state-of-the-art methods, by ensuring the benefit of the method of Lin *et al.* for our specific application.**

[8] `http://visor.udg.edu/i2cvb/`

[9] U. Vovk, F. Pernus, and B. Likar. "A review of methods for correction of intensity inhomogeneity in MRI". in: *Med. Imag., IEEE Trans. on* 26.3 (2007), pp. 405 –421.

[10] S. Viswanath et al. "Integrating structural and functional imaging for computer assisted detection of prostate cancer on multi-protocol in vivo 3 Tesla MRI". in: *Proc. SPIE 7260, Med. Imag. 2009*. Vol. 7260. 2009.

[11] S. Viswanath et al. "Empirical evaluation of bias field correction algorithms for computer-aided detection of prostate cancer on T2w MRI". in: *Proc. SPIE 7963, Med. Imag. 2011*. 2011.

[12] J. G. Sled, A. P. Zijdenbos, and A. C. Evans. "A nonparametric method for automatic correction of intensity nonuniformity in MRI data". In: *Med. Imag., IEEE Trans on* 17.1 (1998), pp. 87 –97.

[13] M. Styner et al. "Parametric estimate of intensity inhomogeneities applied to MRI". in: *Med. Imag., IEEE Trans. on* 19.3 (2000), pp. 153 –165.

[14] M. S Cohen, R. M DuBois, and M. M Zeineh. "Rapid and effective correction of RF inhomogeneity for high field magnetic resonance imaging". In: *Human brain mapping* 10.4 (2000), pp. 204 –211.

[15] M. Lin et al. "A new bias field correction method combining N3 and FCM for improved segmentation of breast density on MRI". in: *Med. Phy.* 38.1 (2011), pp. 5 –14.

[16] M. N. Ahmed et al. "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data". In: *Med. Imag., IEEE Trans. on* 21.3 (2002), pp. 193 –199.

Apart of the bias field, MRI images are also degraded by a Rician noise. Similarly to bias correction, only two CAD systems have filtered the images using wavelet-based techniques[17,18], which offer a proper theoretical baseline for Rician corruption[19]. Non-Local Means-based denoising techniques have extensively and successively been used for other MRI applications, but never for MRI prostate images[20]. **Thus, we will evaluate the Non-Local Means-based techniques[21,22] and wavelet-based technique to select the appropriate method to our application.**

CAD systems are based on machine learning classifiers which are trained to differentiate cancerous from healthy tissue. The classification performance of these classifiers highly relies on the consistency of the dataset. Subsequently, one can emphasize the desire to reduce the inter-patient variability of the MRI dataset. In this regard, each patient dataset needs to be standardised/normalised to a common basis, modality by modality. Only two methods have been used in CAD for prostate: the first method consists in normalising the images via the z-score, while the second technique is based on a linear normalisation by parts[23]. Lemaître *et al.* have developed a normalisation technique using the Rician properties of the MRI signal [24], which outperforms the previous methods for T_2-W-MRI images. **Thus, we will extend this work to the other DCE-MRI and DW-MRI modalities**.

MRSI is a modality related to one dimensional signal, and the enhancing techniques differ from the one used in MRI. The MRSI spectra have to be corrected for several phenomena: phase correction, water and lipid residuals filtering, baseline correction, frequency alignment, and normalisation. This set of enhancement techniques has already been investigated by Lemaître *et al.* in a study focusing solely on the MRSI modality for prostate cancer detection[25]; **this knowledge will be the basis of MRSI enhancement.**

Segmentation To achieve robust cancer detection, the classification has to be carried out only on the prostate area, motivating the need to perform a segmentation of the organ in the MRI images. Furthermore, as mentioned in Sect. 1.1.1, the membership *a-priori* of a voxel to belong to a zone (i.e., PZ or CG) has a high potential to increase the performance to assess the aggressiveness of prostate cancer. Therefore, the prostate zones need to be segmented instead of solely the prostate organ. In this regard, only the work of Litjens *et al.* have segmented the prostate zones using a probabilistic multi-atlas approach[26]. However, the segmentation was performed using only the T_2-W-MRI modality and the ADC map. Although atlas-based methods are robust to intensity variations, they lack of accuracy in the boundary delineations[27]. The potential of machine learning methods to carry out such task is currently underestimated, but has been shown to be suitable in combination with the other approaches (i.e., deformable models or atlas-based)[28]. **Thus, we will design a hybrid system to segment the prostate zones, based on Convolutional Neural Networks (CNN) and Active Shape Models using all multi-parametric images.** The choice of CNN is motivated by the recent breakthrough of deep-learning in multiple fields of computer vision. Deep-learning, however, has still not be extensively used in the field of medical imaging as attested by the organisation of the first workshop specifically dedicated to this topic at MICCAI 2015. Deep-learning relies on a data-driven training stage in which large amount of data

[17] S. Mallat. *A wavelet tour of signal processing, Third Edition: The sparse way*. 3rd. Academic Press, 2008.

[18] A. Pizurica et al. "A versatile wavelet domain noise filtration technique for medical imaging". In: *Med. Imag., IEEE Trans in* 22.3 (2003), pp. 323 –331.

[19] R.D. Nowak. "Wavelet-based Rician noise removal for magnetic resonance imaging". In: *Image Processing, IEEE Transactions on* 8.10 (1999), pp. 1408–1419. ISSN: 1057-7149.

[20] J. V. Manjón et al. "MRI denoising using non-local means". In: *Med. Image Anal.* 12.4 (2008), pp. 514 –523.

[21] J. V. Manjón et al. "New methods for MRI denoising based on sparseness and self-similarity." In: *Med. Image Anal.* 16.1 (2012), pp. 18–27.

[22] P. Coupé et al. "Adaptive Multiresolution Non-Local Means Filter for 3D MR Image Denoising". In: *IET Image Proc.* 11 (2011).

[23] A. Madabhushi and J. K. Udupa. "New methods of MR image intensity standardization via generalized scale". In: *Med. Phy.* 33.9 (2006), pp. 3426 –3434.

[24] This work is submitted for publication.

[25] G. Lemaître. "Absolute quantification at 3 T". MA thesis. Université de Bourgogne, Heriot-Watt University, Universitat de Girona, 2011.

[26] G. Litjens et al. "Evaluation of prostate segmentation algorithms for MRI: the PROMISE12 challenge". In: *Med. Image Anal.* 18.2 (2014), pp. 359 –373.

[27] S. Ghose et al. "A survey of prostate segmentation methodologies in ultrasound, magnetic resonance and computed tomography images". In: *Comp. Met. Prog. Biomed.* 108.1 (2012), pp. 262–287.

[28] S. Ghose et al. "Graph cut energy minimization in a probabilistic learning framework for 3D prostate segmentation in MRI". in: *Pat. Rec. (ICPR), 21st Int. Conf. on*. IEEE. 2012, pp. 125 –128.

are required, which is a serious drawback in medical imaging. However, this problem is addressed by transfer learning which allow to use deep-learning to medical imaging.

Registration In multi-parametric MRI, the data are collected in a sequential manner, involving a possible misalignment between the different modalities. During her PhD at the Universitat de Girona, Mitra *et al.* developed an automatic multi-modal non-rigid registration method[29], which has been shown to outperform the state-of-the-art methods. This method has initially been used for registration between T_2-W-MRI and Ultra-Sound prostate images; **therefore, we will extend this method to align our multi-parametric MRI dataset.**

Detection and assessment Up to now, CAD developed systems solely focus on the detection of prostate cancers, omitting a real assessment of the lesion aggressiveness. The detection of cancers is commonly performed using machine leaning classifiers, designing frameworks as depicted in Fig. 1. These frameworks rely on two compulsory stages and an intermediate optional one: (i) features detection, (ii) features selection/extraction and (iii) features classification. Lemaître *et al.* have extensively reviewed researches carried out in each of this stage for the development of CAD for prostate cancer[30]. These stages are organised in a sequential manner and thus stages upstream part of the features classification have a tremendous importance on the classification performance. Consequently, the use of discriminative features is certainly key and most probably the bottleneck of CAD systems, justifying the attention given by researchers to evaluate multitude of low- and high-level visual features, inspired by computer vision or biology. As aforementioned, deep-learning has been recently shown to be one of the most successful machine learning technique in broad types of classification tasks. CNN has the ability to generate automatically low- and high-level visual features in the network itself[31] by only supplying the raw data as inputs. Furthermore, CNN can be trained using the Gleason grade obtained through biopsy in order to get an assessment of the aggressiveness of the cancer. **Thus, we will detect and assess prostate cancers with CNN. In addition, we will investigate the low- and high-level features to find potential new markers which can be used by clinicians or other machine learning methods.**

Evaluation using PI-RADS The European Society of Urogenital Radiology together with the American College of Radiology have recently published the Prostate Imaging and Reporting and Data System (PI-RADS), which is the standard way to assess and report prostate lesions using multi-parametric MRI. This standard allows to assign a score depending of multiple criteria such as signal intensity, texture, size of lesion, modality, prostate zones, etc. None of the current CAD systems offer a PI-RADS score when detecting potential lesions in multi-parametric MRI. **Thus, we will report the output of our classification framework in terms of PI-RADS score, applying the provided criterion.**

1.2 Clarity and quality of transfer of knowledge/training for the development of the researcher in light of the research objectives

1.3 Quality of the supervision and the hosting arrangements

Qualifications and experience of the supervisor(s)

Career development

1.4 Capacity of the researcher to reach and re-enforce a position of professional maturity in research

2 IMPACT

2.1 Enhancing research- and innovation-related human resources, skills, and working conditions to realise the potential of individuals and to provide new career perspectives

In this section, please explain the impact of the research and training on the Experienced Researcher's career. The fellowship, including any secondments in Europe should maximise the impact on the researcher's activity on European society, including the science base and/or the economy, in a manner appropriate to the research field.

[29] J. Mitra et al. "A spline-based non-linear diffeomorphism for multimodal prostate registration". In: *Med. Image Anal.* 16.6 (2012), pp. 1259 –1279.

[30] Lemaître et al., "Computer-Aided Detection and Diagnosis for Prostate Cancer based on mono and multi-parametric MRI: A review".

[31] M. D. Zeiler and R. Fergus. "Visualizing and Understanding Convolutional Networks". In: *CoRR* (2013).

2.2 Effectiveness of the proposed measures for communication and results dissemination

Required sub-headings:

Communication and public engagement strategy of the action
Dissemination of the research results
Exploitation of results and intellectual property

Concrete plans for the above must be included in the Gantt Chart. The new knowledge generated by the action should be used wherever possible to enhance the career of the researcher, to advance research, to foster innovation, and to promote the research profession to the public. The following sections of the European Charter for Researchers refer specifically to public engagement and dissemination:

Public engagement Researchers should ensure that their research activities are made known to society at large in such a way that they can be understood by non-specialists, thereby improving the public's understanding of science. Direct engagement with the public will help researchers to better understand public interest in priorities for science and technology and also the public's concerns.

Dissemination, exploitation of results All researchers should ensure, in compliance with their contractual arrangements, that the results of their research are disseminated and exploited, e.g. communicated, transferred into other research settings or, if appropriate, commercialised. Senior researchers, in particular, are expected to take a lead in ensuring that research is fruitful and that results are either exploited commercially or made accessible to the public (or both) whenever the opportunity arises.

3 IMPLEMENTATION

3.1 Overall coherence and effectiveness of the work plan

The proposal is separated into 7 work packages:

WP1: Data acquisition and dissemination (duration of 5 months) **T1.1** Preparation of the multi-parametric MRI dataset

T1.1 Preparation of the multi-parametric MRI dataset

WP2: Pre-processing (duration of 7 months)

WP3: Segmentation (duration of 7 months)

WP4: Registration (duration of 7 months)

WP5: Detection and assessment (duration of 8 months)

WP6: PI-RADS evaluation (duration of 2 months)

WP7: Communication (duration of 36 months)

3.2 Appropriateness of the management structure and procedures, including quality management and risk management

Develop your proposal according to the following lines:

- Project organisation and management structure, including the financial management strategy, as well as the progress monitoring mechanisms put in place;
- Risks that might endanger reaching project objectives and the contingency plans to be put in place should risk occur.

The following could be also included in the Gantt Chart:

- Progress monitoring;
- Risk management;
- Intellectual Property Rights (IPR).

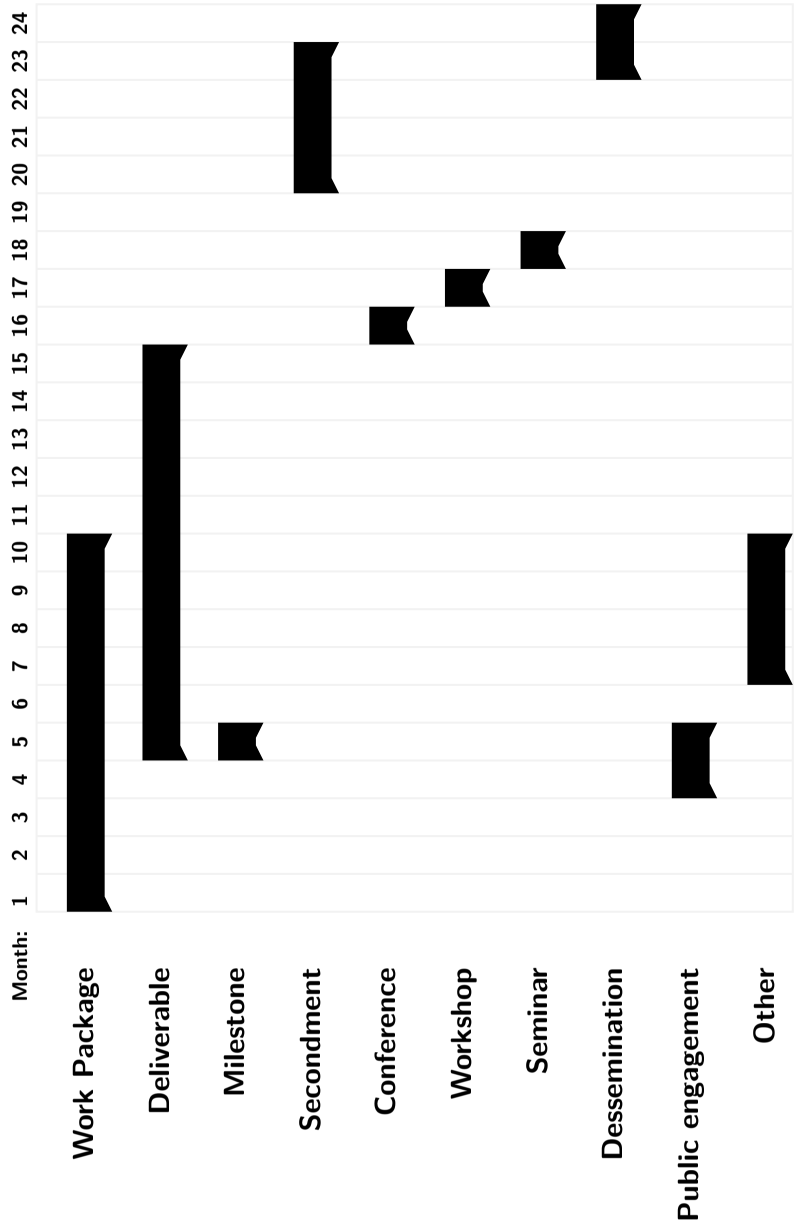

Figure 2: Example Gantt Chart

3.3 Appropriateness of the institutional environment (infrastructure)

Give a description of the legal entity/ies and its main tasks (per participant). Explain why the fellowship has the maximum chance of a successful outcome.

NB: Each participant is described in Section 6. This specific information should not be repeated here.

3.4 Competences, experience and complementarity of the participating organisations and institutional commitment

Here describe how the fellowship will be beneficial for both the Experienced Researcher and host organisation(s).

- Commitment of beneficiary and partner organisations to the programme (for partner organisations, please see also section 6)

Partner organisations: The role of Partner organisations in MS/AC for secondments and their active contribution to the research and training activities should be described.

4 CV OF THE EXPERIENCED RESEARCHER

4.1 PERSONAL INFORMATION

Name: Guillaume Lemaître
Date of birth: 27th April 1988, 27 years old
Personal website: `https://sites.google.com/site/glemaitre58`

4.2 EDUCATION

07/2012 — 12/2015 **Co-joint PhD in Medical Imaging**
"Computer Aided Diagnosis system for prostatic biopsy guidance and follow-up fusing multi-modal imaging"
Supervised by Dr. R. Martí, Prof. F. Mériaudeau, Dr. J. Freixenet, and Dr. P. M. Walker
ViCOROB, Universitat de Girona — LE2I, Université de Bourgogne

09/2012 — 09/2014 **Master in Business Innovation and Technology Management**
"Valorisation of computerized technology in the health care sector"
Supervised by Dr. A. Bikfalvi and Dr. J. Llach
Universitat de Girona

09/2009 — 06/2011 **Master of Excellence Erasmus Mundus in Vision and Robotics**
"Absolute Quantification in 1H MRSI of the Prostate at 3.0 T"
Supervised by Dr. P. M. Walker
Université de Bourgogne, Universitat de Girona, Heriot-Watt University

09/2016 — 09/2009 **Bachelor Eng. Electronic, Signal, and Image**
Université de Bourgogne

4.3 WORKING EXPERIENCE

03/2015 — 01/2016 **Assistant professor (ATER)**
184 hours of lecturing in databases, pattern recognition and machine learning, programming, image processing
Université de Bourgogne

06/2011 — 06/2012 **R&D researcher**
Barcelona Digital — ViCOROB, Universitat de Girona

4.4 FELLOWSHIPS AND AWARDS

4.5 PARTICIPATION IN PUBLIC-FUNDED PROJECTS

- Temporal analysis and automatic detection of lesions in multi-modal images (IA-BioBreast)
- OCT imaging
- Erasmus+ Early Mastery project

2012	**OMJ Grant**, Minitère Français des Affaires Etrangères et Européennes, France
2012	**FI-DGR PhD Grant**, Generalitat de Catalunya - AGAUR, Spain
2011	**Research Master Scholarship**, Burgundy Region, France
2010	**Erasmus Spanish Scholarship**, Spanish Ministry, Spain
2010	**Merit-based Scholarship**, French Ministry, France
2010	**Merit-based Scholarship dedicated to Research Masters**, Burgundy Region, France
2009	**Spanish Ministry Mobility Scholarship**, Spanish Ministry, Spain
2009	**Merit-based Scholarship**, French Ministry, France
2009	**Erasmus French Scholarship**, French Ministry, France
2009	**Mobility Grant**, Burgundy Region, France
2009	**Region Mobility Scholarship**, Burgundy Region, France
2009	**Rotary Scholarship**, Rotary Club Le Creusot, France
2009 — 2011	**Erasmus Mundus Grant**, Heriot-Watt University, Universitat de Girona, Université de Bourgogne, Scotland, Spain, France
2008	**Erasmus French Scholarship**, French Ministry, France
2008	**Mobility Grant**, Burgundy Region, France

July, 2008	**Student Autonomous Underwater Competition - Europe**, Nessie III - Heriot-Watt University
July, 2008	**THALES Special Award for innovation**, Nessie III - Heriot-Watt University

4.6 TEACHING

24 h **Medical Imaging: Segmentation and registration methods**
Master Erasmus Mundus ViBOT
Universitat de Girona

24 h **Pattern Recognition and Machine Learning**
Master Erasmus Mundus ViBOT
Université de Bourgogne

48 h **Introduction to image processing**
Master Erasmus Mundus ViBOT
Université de Bourgogne

16 h **Software engineering**
Master Erasmus Mundus ViBOT
Université de Bourgogne

74 h **Introduction to databases**
Bachelor of Electrical Engineering
Université de Bourgogne

4.7 SUPERVISION

- Supervision of 3 BSc. and MSc. students during their summer internships

4.8 PUBLICATIONS

Peer-Review Journals Papers:

1. **G. Lemaitre, R. Marti, J. Freixenet, J. C. Vilanova, P. M. Walker, and F. Meriaudeau**, "Computer-Aided Detection and Diagnosis for prostate cancer based on mono and multi-parametric MRI: A Review", *Computer in Biology and Medicine*, vol. 60, pp 8 - 31, 2015. **(Citations: 3)**

Peer-Review International Conferences Papers:

1. **A. Meyer-Baese, J. Massich, G. Lemaitre, and M. Rastgoo**, "Real-Time Optical Flow with Theoretically Justified Warping Applied to Medical Imaging", *Breast Image Analysis Workshop (BIA), Medical Image Computing and Computer Assisted Interventions (MICCAI) 2015*. Munich: Germany (Oct. 2015). **(Citations: 0)**

2. **J. Massich, G. Lemaitre, J. Marti and F. Meriaudeau**, "An Optimization Approach to Segment Breast Lesions in Ultra-Sound Images using Clinically Validated Visual Cues", *Breast Image Analysis Workshop (BIA), Medical Image Computing and Computer Assisted Interventions (MICCAI) 2015*. Munich: Germany (Oct. 2015). **(Citations: 0)**

3. **G. Lemaitre, M. Rastgoo, J. Massich, S. Sankar, F. Meriaudeau, and D. Sidibe**, "Classification of SD-OCT volumes with LBP: Application to DME detection", *Ophthalmic Medical Image Analysis Workshop (OMIA), Medical Image Computing and Computer Assisted Interventions (MICCAI) 2015*. Munich: Germany (Oct. 2015). **(Citations: 0)**

4. **J. Massich, G. Lemaitre, J. Marti, and F. Meriaudeau**, "Brest Ultra-Sound image Segmentation: an Optimization approach based on super-pixels and high-level descriptors", *International Conference on Quality Control and Artificial Vision (QCAV) 2015*. Le Creusot: France (Jun. 2015). **(Citations: 0)**

5. **G. Lemaitre, J. Massich, R. Marti, J. Freixenet, J. C. Vilanova, P. M. Walker, D. Sidibe, and F. Meriaudeau**, "A Boosting Approach for Prostate Cancer Detection using Multi-parametric MRI", *International Conference on Quality Control and Artificial Vision (QCAV) 2015*. Le Creusot: France (Jun. 2015). **(Citations: 0)**

6. **G. Lemaitre, A. Bikfalvi, J. Llach, J. Massich, and F. Julian**, "Business Model Design for University Technology Valorisation", *International Technology, Education and Development Conference (INTED) 2015*. Madrid: Spain (Mar. 2015). **(Citations: 0)**

7. **M. Rastgoo, G. Lemaitre, X. Rafael, F. Miralles, and P. Casale**, "Pruning AdaBoost for Continuous Sensors Mining Applications", *Ubiquitous Data Mining Workshop, 20th European Conference in Artificial Intelligence 2012*. Montpellier: France (Aug. 2012). **(Citations: 2)**

8. **G. Lemaitre, E. Vargiu, J.A. Lorenzo FernÃąndez, and F. Miralles**, "Real-Time 2D Face Detection and Features-based Tracking in Video", *IADIS Multi Conference in Computer Science in Computer Graphics, Visualization, Computer Vision and Image Processing 2012*. Lisbon: Portugal (Jul. 2012), 2012. **(Citations: 0)**

9. **J. Cartwright, N. Johnson, B. Davis, Z. Qiang, T.L. Bravo, A. Enoch, G. Lemaitre, H. Roth, and Y. Petillot**, "Nessie III Autonomous Underwater Vehicle for SAUC-E 2008", *The Unmanned Underwater Vehicle Showcase (UUVS)*, 2008. **(Citations: 5)**

5 CAPACITIES OF THE PARTICIPATING ORGANISATIONS

All organisations (whether beneficiary or partner organisation) must complete the appropriate table below. Complete one table of maximum one page for the beneficiary and half a page per partner organisation (min font size: 9). The experts will be instructed to disregard content above this limit.

Beneficiary X	
General Description	
Role and Commitment of key persons (supervisor)	(Including names, title, qualifications of the supervisor)
Key Research Facilities, Infrastructure and Equipment	(Demonstrate that the team has sufficient facilities and infrastructure to host and/or offer a suitable environment for training and transfer of knowledge to recruited Experienced Researcher)
Independent research premises?	
Previous Involvement in Research and Training Programmes	
Current involvement in Research and Training Programmes	(Detail the EU and/or national research and training actions in which the partner is currently participating)
Relevant Publications and/or research/innovation products	(Max 5)

Partner Organisation Y	
General Description	
Key Persons and Expertise (supervisor)	
Key Research facilities, infrastructure and equipment	
Previous and Current Involvement in Research and Training Programmes	
Relevant Publications and/or research/innovation product	(Max 3)

ENDPAGE

MARIE SKŁODOWSKA-CURIE ACTIONS

Individual Fellowships (IF)
Call: H2020-MSCA-IF-2015

PART B

"ProDeepCAD"

This proposal is to be evaluated as:

[Standard EF]