Autonomy of robots often requires an internal representation of the current state of both the robot and its environment. For instance, a mobile robot aiming to go at a specific location will often estimate its current location and the map of the place; a robotic arm trying to pick an object will need the pose of the object (position and orientation), the description of potential obstacles, and its own current configuration; a humanoid robot in interaction with a human will need to know what the human is currently doing, her pose, her intention, her emotional state... Standard state estimation techniques often rely on a probabilistic representation wherein a probability distribution over the state space is recursively computed based on some observations and a model of the evolution of the system. This is generically known as a Bayesian filter, which has several classical instantiations according to the specificities of the system. Typical examples cases are Hidden Markov Models for discrete state representation and full transition matrices [Rabiner, 1989], Kalman filters for continuous states with Gaussian distributions and linear models [Kalman, 1960], or even particle filters for a sampled representation of the distributions [Doucet et al., 2000]. These techniques have been applied for distinct parts of the estimation either of the state of the robot with embedded sensors [Kubelka et al., 2015, Hitz et al., 2016], for the estimation of the robot with distributed sensors [Rio et al., 2016], for the estimation of human activity [Dubois and Charpillet, 2013] or sound sources [Nguyen et al., 2016], or even mapping the environment [Durrant-Whyte and Bailey, 2006]. As expected various representations are suited for different purposes.

The key challenge comes when fusing information from multiple sources of different characteristics. Classically, either you opt for a single system with the full state and all sensors in a monolithic filter, or you choose a specific representation shared across all sub-filters that can be treated together in a weak-fusion scheme. This works well until you need to build a integrated representation of both the robot and the environment based on various modalities and processes. For instance, it is important to jointly work with discrete probabilities, Gaussian or mixture of Gaussian distributions, and particles in order to build a representation of the environment including an occupancy map of the obstacles, the location of sound sources and of several persons with different activities, and the current state of the robot based on the results in the literature.

A second challenge is to be able to integrate machine learning prediction into the model-based filters. Indeed, as the world representation becomes more complete it becomes more difficult to
specify relevant models. A solution can be to completely resort to machine learning, not even attempting to specify any model, but it would be better to reuse the models we already have despite their shortcomings and use machine learning as a complement.

**References**


**Main activities**

**Project description**

The aim of this PhD project is therefore to advance the state of the art of filtering techniques in robotics along two principal dimensions.

The first objective is to find way to propagate information between the different kinds of filters: how to do efficient Bayesian inference with distinct distribution representations? An approach of this question could typically come from approximation techniques such as sampling or moment matching.

The second objective will be to combine those model-based filtering techniques with machine learning. Indeed the models are never complete or correct and several techniques require approximations to become tractable. There are therefore systematic errors that could potentially be corrected by model-less learning techniques such as deep neural networks. This second objective requires again to be able to transfer information across different kind of representations.

Finally, the emphasis will be laid on the experimentation and validation methodology. The algorithms developed should be demonstrated and applied to concrete robotics problems, for instance in the context of the smart apartment. This experimental setup is a small flat equipped with a wide range of sensors from pressure tiles on the ground to RGB-D cameras. We dispose of several mobile robots from turtlebots to a Pepper robot as well as a motion capture system that can provide ground truth information for the pose of the robots and of humans. Right now, we can separately locate the robot, build a map of the obstacles, locate sound sources, locate people and assess their current activity, etc. The aim...
is to build an integrated representation of this all and to leverage the synergies to improve their respective estimates. Indeed, knowing that there is somebody at a given place in the environment might give a hint about the location of a sound because it might come from a device she operates. Furthermore, the identification of this sound could help for the activity recognition.

**Skills**

**Required qualifications**

MSc in computer science, robotics, or automation with strong skills in robotics, Bayesian or probabilistic inference, and programming (C++ or Python).

**Language**

French or English.

**Benefits package**

- Subsidised catering service
- Partially-reimbursed public transport
- Social security
- Paid leave
- French courses

**Remuneration**


Monthly salary after taxes: around 1596,05€ for 1st and 2nd year. 1678,99€ for 3rd year. (medical insurance included).