ABSTRACT:

Name of Responsible Researcher:	**Dr. Sergio Uribe Arancibia**
Proposal Title:	**Physics-Informed Neuronal Networks applied to Inverse Problems in Hemodynamics from Medical Images**

Hemodynamics is the study of blood flows, and the best way to visualize these flows is via cardiac Magnetic Resonance Imaging (MRI). This technique has proven to be valuable in diagnosing several cardiovascular conditions, such as congenital/vascular/valvular heart diseases, myocardial infarction ischemia, and myocarditis. One common MRI technique is the 2D cine Phase-Contrast MRI (PC-MRI), which can measure the in-plane blood flow velocity through a specific plane. More recently introduced techniques such as "4D Flow MRI", are capable of measuring the entire 3D velocity field, and thus allow a more comprehensive study of the flow and its quantification. However, these newer methods suffer from having long scan times and complex post-processing stages.

The use of increasing volumes of hemodynamic data is very challenging. Computational Fluid Dynamics (CFD) has played a bridging role between medical image acquisition and medical flow quantification. Inverse problem methods have been used for modeling cardiovascular flows and for computational parameter extraction. However, CFD is usually highly dependent on the boundary conditions and is sensitive to geometrical domain accuracy. Moreover, computation times can be high even on high-performance computing machines. For these reasons, CFD is currently not used to support clinical decision-making.

Machine learning is the capacity of computers to learn from data. In particular, deep learning uses artificial Neural Networks (NNs) to extract knowledge from training data and to represent it. Nowadays, NNs obtain state-of-the-art performance in most areas of knowledge. Nevertheless, current NN architectures do not automatically encode physical principles behind processes, such as energy conservation, and thus cannot assure that the solutions do not violate these principles. For this reason, in recent years, Physics-Informed Neural Networks (PINNs) have attracted enormous interest.

Here I propose to apply PINNs to solve fundamental inverse problems in cardiovascular hemodynamics. Recent literature suggests that PINNs can be a powerful method for predicting physical parameters such as lumped parameters, wall-shear stress, and pressure fields from low-resolution PC-MRI images. Moreover, the time required by PINNs could be thousands of times shorter than CFD approaches.

The PINNs will be constructed so that no high-quality images are needed, avoiding a potentially high-cost training stage. To this aim, I propose a decoupled architecture between trained network parameters and fluid state variables, which promotes multivariate learning. Furthermore, the NN solutions for blood velocity and pressure will be coupled to the Navier-Stokes equations in physics-informed learning. This whole structure has shown great potential for recovering the state variables of the fluid even in cases where the physics is only partially known.

Comparison to sequential Kalman Filter methods will be used to validate the performance of our new PINN methods: both methodologies will be tested on synthetic and real data experiments, featuring 2D and 3D PC-MRI measurements on the aorta artery. The versatility of PINN architectures allows to treat a large class of inverse problems, including velocity reconstruction and parameter estimation problems such as lumped boundary conditions, wall shear-stresses, and pressure fields.

It is expected that the PINNs, once fully well-trained, will outperform the Kalman Filter method in terms of computational time with similar output quality of the results. Also, with the help of transfer learning techniques, it is expected that the PINNs can be fine-tuned to each volunteer, with short adaptation times between different patients. This research will become an excellent opportunity to make computational hemodynamics closer to the clinical world, where deep learning techniques have become increasingly necessary.