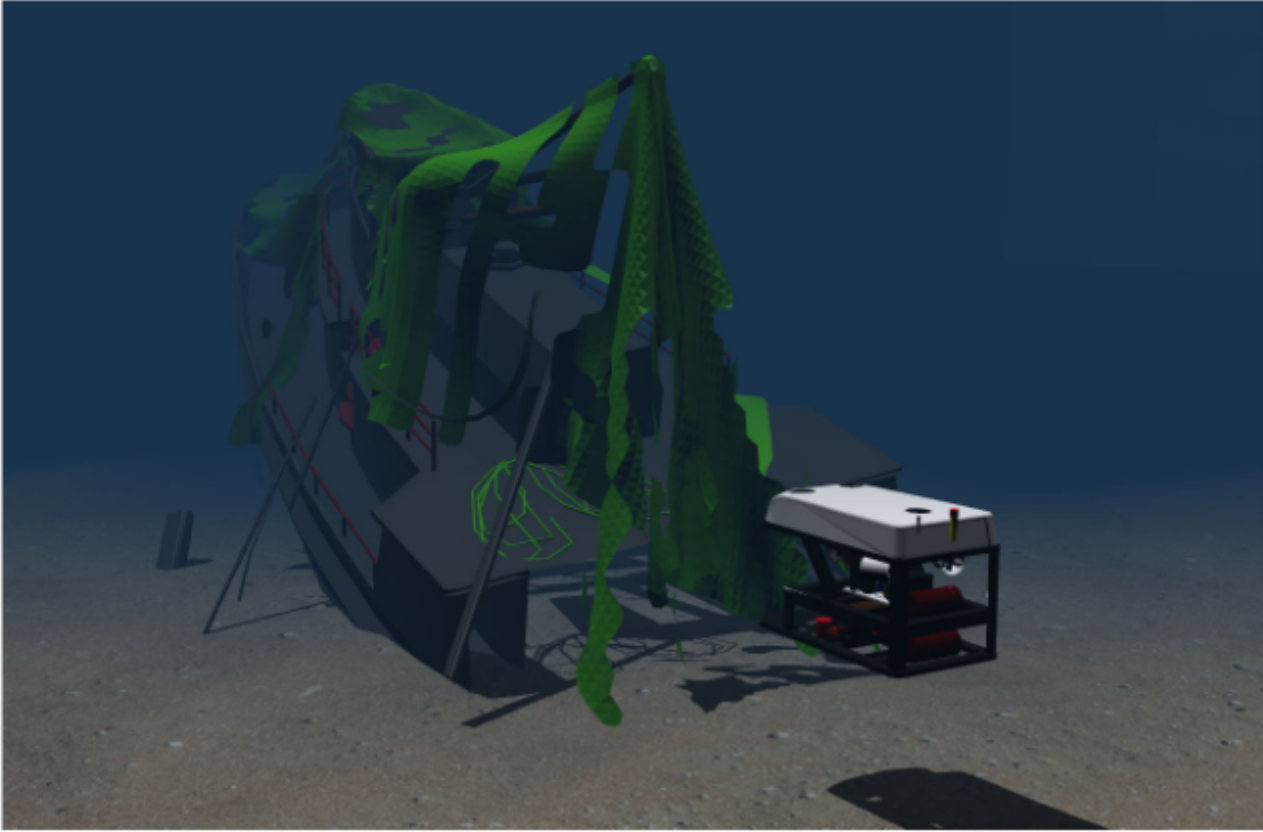


Одно из интересных направлений применения ИИ, не банкирами, чтобы человечкам кредиты впаривать или всяким ухарям дипфейки генерить (чтобы что?), а это конечно системы навигации без использования внешних коммуникаций.

Французы вовсю сейчас тренируют свои железные мозги для того чтоб.

Вот идея:



**FIGURE 1.** The RexRov2 platform simulated in Gazebo.

### **A. DESIGN OF THE MODEL-BASED PART OF THE CONTROLLER**

The complete modelling of the RexRov2 platform is challenging [5], [38], but it can be summarised in the state-space representation form [22] as:

$$\begin{aligned} \dot{\eta} &= J_{\Theta}(\eta)v, \\ M\dot{v} + C(v)v + D(v)v + g(\eta) &= \delta + \delta_{cable}, \end{aligned} \quad (4)$$

where  $\eta$  and  $v$  are the position and velocity vectors

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1.6.1.

Создали виртуальную подводную реальность с различными препятствиями и в ней гоняют "биоподобные" ( очень грубо говоря - два уровня обучения с кратковременной и долговременной памятью ) которые должны ориентироваться по реперным точкам или ориентировочной карте ландшафта, ну и имеющимся в наличии "приборам" , а также если в стае то через общение между собой ( не в этой статье )

no exhaustive hyperparameter tuning was required. The PyTorch framework and CUDA toolkit were used to implement this architecture along with an Nvidia RTX 2070 GPU card for gradient and simulation processing. The ANNs were optimised using the standard Adam method and regularisation techniques were used to prevent overfitting. It has been demonstrated that regularisation does matter for Policy Gradient methods [20]. Following these results, we added regularisation to the critic NN only by means of a weight degradation of 0.001. Given that this work uses the maximum entropy framework, no further regularisation was applied to the actor NN. The learning rate for all networks was set to  $l_r = 3e^{-4}$ . The Leaky ReLU activation function was applied to all hidden layers and gradient descent was performed using a mini-batch of size 256. Layer normalisation [4] was added before the activation function of all hidden layers. The weights and biases were initialised from the Gaussian distribution  $\mathcal{N}(0, \sqrt{2/f})$ , where  $f$  is the input of the layer.

#### IV. A BIO-INSPIRED EXPERIENCE REPLAY (BIER)

The Biologically-Inspired Experience Replay (BIER) method, proposed in this work, assumes two distinct memory units: the sequential-partial memory (**B1**), which stores incomplete temporal sequences, and the optimistic memory (**B2**), that emphasises the best transitions as measured by the reward with respect to the current policy. As illustrated in Figure 2, BIER takes advantage of the resilience of the on-policy sampling while maintaining the efficiency of the data from the off-policy formulation.

Buffer **B1** has a similar function to the memory buffer used in the original definition of ER in reinforcement learning. In a robotic domain, the optimal behaviour is highly temporally correlated, since early action sequences have a more pronounced effect on future gains. In addition, a vehicle's behaviour is bounded by the natural constraints of its actuators. Thus, the shape and number of possible

improving the learning

The optimistic memory is inspired by the observation that an optimistic policy is more efficient in exploring new regions (as measured by the performance [21]). However, a large replay buffer size increases the probability of selecting sub-optimal actions, slowing down performance. Buffer **B2** is to be optimistic by focusing on the best past transitions associated with the current solution space.

Buffer **B2** stores the transitions that are considered to be the best. The set point can be defined according to the nature of the variable. It is that the shape of the transition is *a priori*. For instance, in a robotic domain, the closer the vehicle is to the maximum value of the reward, the optimal policy should be (the shape). In practice, however, the set point, the more the errors (which is measured by the reward). Depending on the system, the reward function (among other things) can assume various shapes. The metric not robust to different shapes. In this work considers a transition stored in **B2** if its associated with the expected future rewards. The value  $\mathbb{E}[r(s_t)]$  is computed for the transitions generated that are stored in **B2**. The size of  $M$  was chosen to be 1000. A moving window of 100

"Траектория" понятна - как обучат так выпускают в воду - если помните писал про рыб роботов в доме пионеров

<https://aftershock.news/?q=node%2F1056942>

или подводный дрон за две минуты

<https://aftershock.news/?q=node%2F1229848>

Есть вопрос по поводу энергии для движения вот этих рыбок гуппи, батарейки быстро сядут... но тут идей много, основная из "подводных течений" извлекать - вот слайды из которых понятно о чем речь

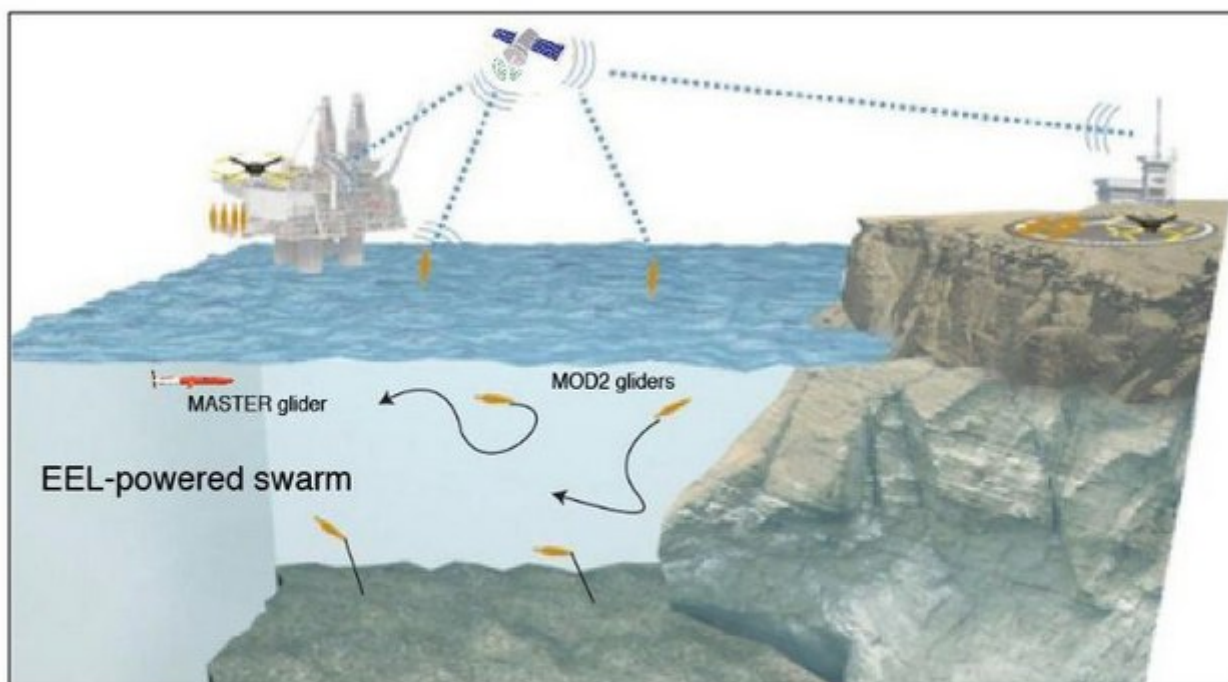


Figure 1. Proposed subsea swarm of EELs. Original artwork by Pyro-E.

Table 1. Projected Power Budget: Generation.

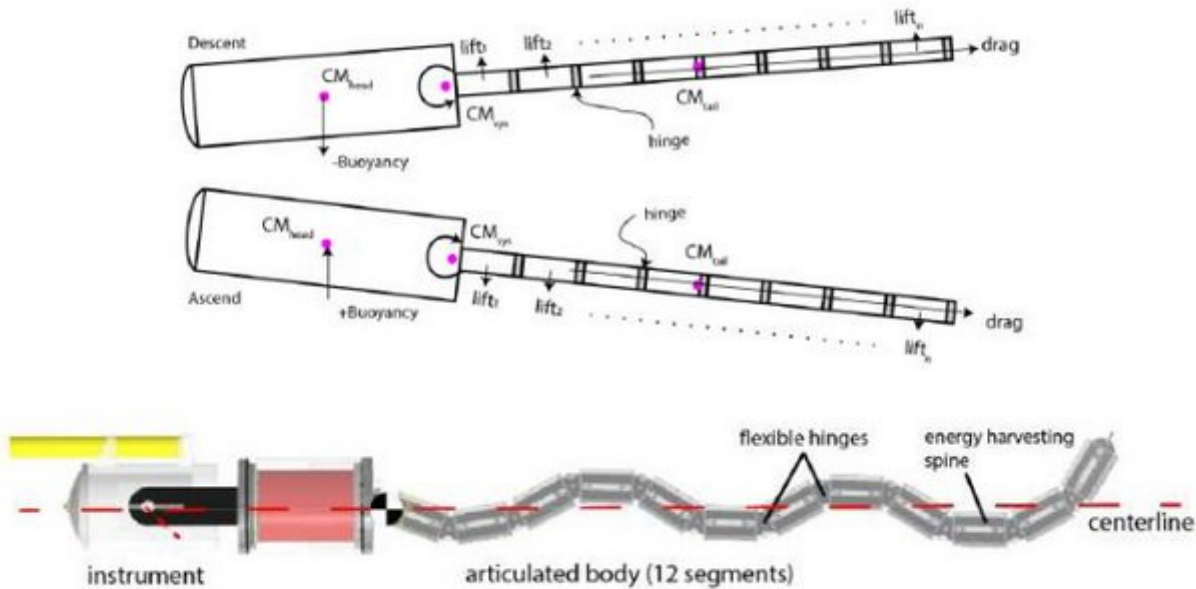
	Nominal Capacity	% Duty Load	RMS Power
Mode: Station-Keeping	8.19 W	20%	1.64 W
Mode: Passive Gliding	4.10 W	80%	3.28 W
<b>Total Generation</b>			<b>4.92 W</b>



**Table 4. Station-Keeping Modes and Excitation Regimes.**

	H = 0.05 m	H = 0.1 m	H = 0.2 m	H = 0.4 m	H = 0.8 m	H = 1.6 m
T = 1 s	Small Excitation	Medium Excitation			Large Excitation	
T = 3 s						
T = 9 s						

In this mode, EEL will be submerged at a shallow depth below the free surface of water. The kinetic energy of subsurface currents is to be harvested by EEL at depths up to a few meters and converted to electric current. In simulations, it is assumed that this depth is less than 2 m. To represent ambient waves and resulting excitation in a representative domain, the conditions listed in Table 4 are used.

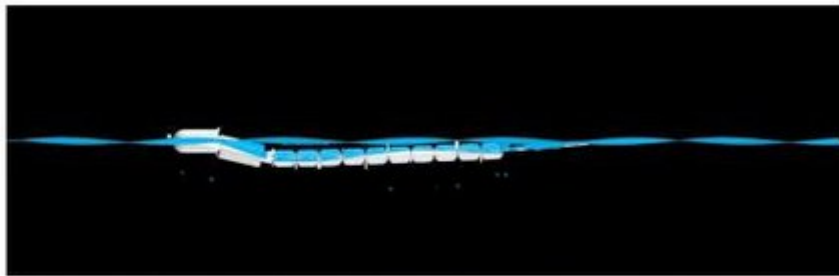


**Figure 3. Hydrodynamic forces acting on EEL prototype, proposed by Pyro-E.**

Preliminary study by Pyro-E with low-fidelity coupled fluid structural simulations using Ansys Mechanical/Fluent was conducted for the preliminary design parameters of EEL. The numerical analysis

Тут без виртуальности сделали в железе

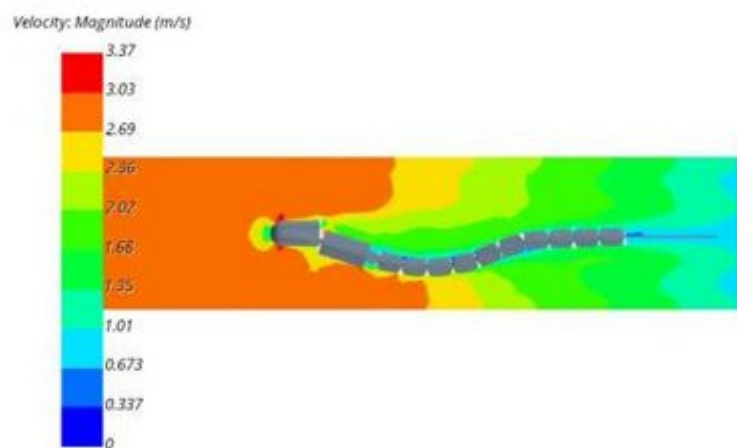
to be relayed through the segments and hinges towards the tail to generate sufficient deformation.



(a) EEL in motion: tail near free surface, segments and head submerged



(b) EEL tail exhibiting low flexibility with peak solid displacement less than 1 mm



(c) Velocity field around EEL showing high velocity flow at curved surfaces of the head body

Figure 9. EEL design in vertical orientation.

3.1.2.2 *EEL Orientation for Horizontal Oscillation:* In a horizontal orientation, EEL performed noticeably better in terms of qualitative agreement with test observations, as well as agreement with quantitative displacements of similar magnitude. This comparison is shown in Figure 10.

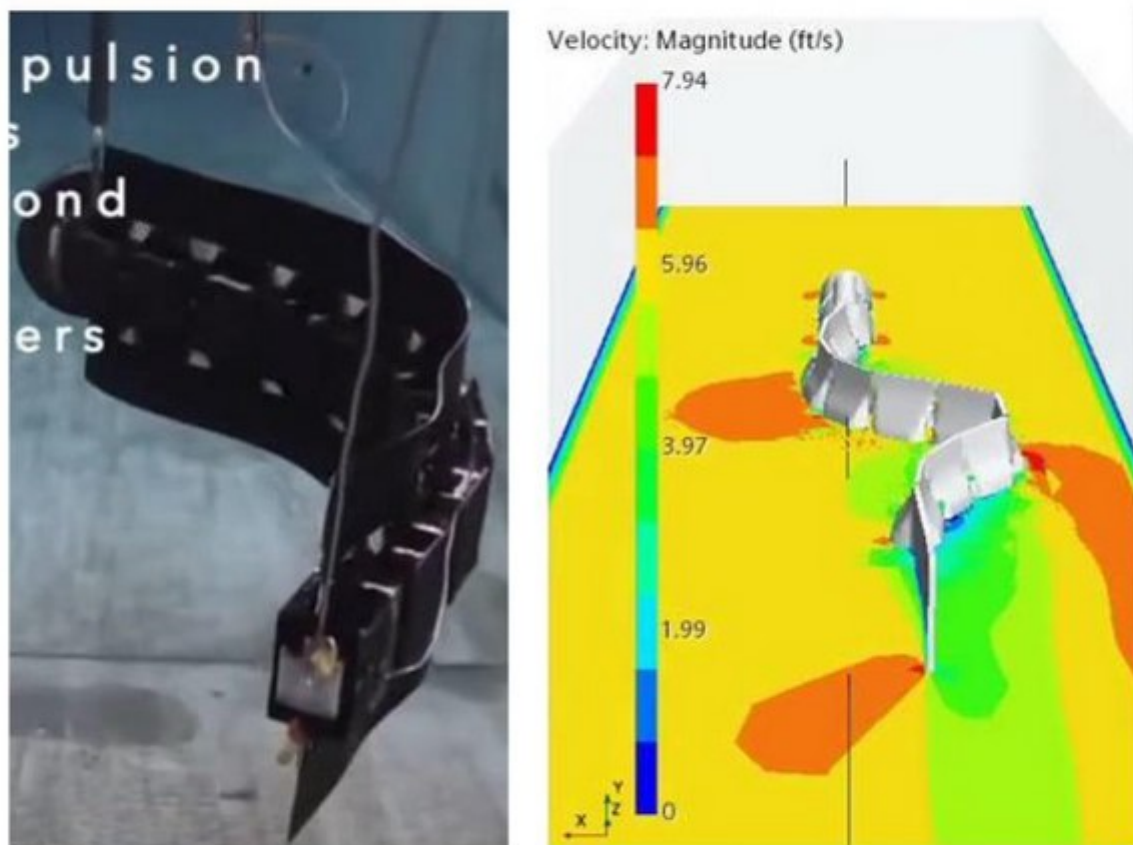


Figure 10. A comparison of hydrodynamic response for EEL between test and simulation.

Despite larger oscillations of the EEL segments and tail initially away from the prototype centerline, the tail was once again found to exhibit unfavorable stiffness. This stiffness once again led to numerical instabilities

Вот слева на фото.

В озерах такое работать конечно не будет... ну может и хорошо.

Но что стоит отметить - если все будет идти так как идет сейчас, то глобальная морская торговля будет рано или поздно разрушена (увы в том числе севморпуть и аналоги) ПОЛНОСТЬЮ!

Так как это все, ну очень дешево, особенно если в серию запускать и не студентами, а корпами.

На суше как то безопасней что ли.

P.S.

В комментах правильное замечание по поводу гравитационной карты - но тут речь конечно скорее просто об ориентации при выполнении работ.... и получение своего положения для координации с другими если в стае идут.