Vision, Perception and Intuition in structural analysis

Fabio Bazzucchi[1,2][0000−0002−2624−6944]

[1] Senseable City Lab, Massachusetts Institute of Technology, Cambridge, MA.
fbaz@mit.edu
[2] Politecnico di Torino, DISEG, Department of Structural, Geotechnical and Building Engineering, Corso Duca Degli Abruzzi, 24, Turin 10128, Italy.

Abstract. Forces geometric visualization and representation in one of the key aspects in Structural Mechanics and its advancement went along with the progress of the subject itself. From graphic statics to modern Computer Vision (CV) systems, there is a constant and significant component of the visual factor when compared to other disciplines in the STEM panorama. In this work, I present the experience carried on in the MSCA FORSEES to try to frame and quantify this visual factor. I will then suggest a new perspective to the problem of forces identification (and related stress and strain) in solids based on some recent discoveries in Neuroscience. The analogy that represents the first step of this exploration is between the Free Energy Principle (FEP) [1] and the Elastic Potential Energy, by defining a structure behavior as the inner agent to sustain structural integrity. Limiting the FEP to the visual sense only [2], we will look through the indissoluble link that lies within the relation of a form and its structural behavior, circling back to the base of the Theory of Elasticity. Final step will be the application to common methods in engineering practice and teaching of AI-based visual tools for structural analysis.

Keywords: free energy principle · visual cognition · FEMA · rapid visual screening · intuitive structural analysis.

1 Introduction

Professor Baldacci's book [3] on Mechanics of Solids famously begins by introducing the stress and strain tensors as models of the mind. They represents a generalization of the empirical observations in a purely mental construct, that when examined in its ideal dimension, produces relations inaccessible for the experience but deductible through inference. As in a perfect Kantian critique approach, these models are bounded and controlled by experience on the relations that they produce, and not on their logical framework [4], [5]. Cauchy stress tensor formulation is in fact axiomatic [6] and based on the mathematical institution of the stress entity $\mathbf{t}_n$. In a specific point of a continuum solid in equilibrium, it is always possible to define the ratio

$$\mathbf{t}_n = \lim_{A_n \to \infty} \frac{\mathbf{R}_n}{A_n}, \tag{1}$$

where $\mathbf{R}_n$ is the resulting force on the small area A_n identified by the normal n. Tetrahedral decomposing of $\mathbf{t}_n$ provide the special components and the terms of the stress tensor. The extension of it to the whole solid domain has two crucial assumptions: *(i)* the limit expressed by 1 exists for every small value of A_n, sacrificing atomic or sub-atomic behavior characterization in favor of the experience representation. And *(ii)*, the properties observed at infinitesimal scale are the same that the ones observed in the solid macrocosms, implying that structural analysis is indeed a phenomenological analysis.

This line of reasoning nimbly overcome the debate between Rationalists and Empiricist, decoupling reality from its elemental representation (*à la* Mach) and mathematical nesting. The elision of this unnecessary harmony, highlighted by Poincaré [7] in a visionary way, resonates with current Machine Learning (ML) and Artificial Intelligence (AI) methodologies. By training models on a large number of certified phenomenological observations, the solving agent infers the results of a new experience, and their fitness is only assessed on the empirical validity of them. We, for example, define a good Neural Network (NN) the one that has a better statistical accuracy on the data, not the one that has an inherent reality representation [8], [9]. This quasi-metaphysical epistemology finds even more reverberation in the Consciousness studies and Mind modeling [10], [11], [12]. It is in fact necessary, not for a relativism but for a centrality of the mind, to pass from reality to reality mental representation. To do so, the concepts of Markov Blanket (MB) and Intelligence have to be introduced [13], [14], [15]. For the scope of this work, we can see a MB as the boundary that encompass and separates the Intelligence from all the rest, i.e. the reality. On its surface, the MB contains the organs for reality perception and interaction. Under the light of this, the Intelligence creates and stores a mental image of the reality through the filter of the sensing and interacting apparatuses. If we consider the example of the human vision sense, vision is the task performed by the MB dedicated organs while perception is the feedback processed knowledge by the brain through cognition [16]. However, the brain is capable of fast MB interactive responses without a significant cognitive work, and relying of some presets and constructs of the Intelligence: intuition [17].

Circling back to the initial problem of structural analysis, we can say that a mind model such the stress tensor is not a construct built by the Intelligence through active (sensing and interacting) perception, but a construct produced by pure cognition. The inference that the intelligence may perform are the relations of this construct, that has the sole boundary of creating coherent results with consensus empirical observation. In other words, we may assume that the use of axiomatic mind models forces the constructivism of the mind and the development of intuitive schemes. This hypothesis is easily verifiable for trusses deform drawings, in where few axioms help to predict the deformation of structural systems. Visual analysis had in fact a major importance in the heroic stage of structural analysis, from internal action representation to the immense work in

Graphic Statics [18], [19]. Finite Element Method stopped the advancements and the discourse around such approaches in favor of a more rationalist approach, but they are now going through a revival phase. Apart from their use in form finding [20], Computer Vision (CV) is displaying all is power in recognition, detection and classification tasks. In this work, the potential of CV in structural analysis is presented and connected with intuitive-like solutions approach.

2 Structural integrity and FEP

A well renowned and solid model for brain inference is Karl Friston Free Energy Principle (FEP) [21], [16], [22]. For what concerns the scope of this work, we can use the FEP intrinsic derivation of the best mental image of the reality through a minimization of the free energy, thus the maximizion of the likelihood between the sensed form and the interactive form. The free energy can be expressed as follow

$$F(s,\mu) = E_q[-\log p(s,\psi|m)] - H[q(\psi|\mu)] = \\ [-\log p(s|m)] + D_{KL}[q(\psi|\mu)||p(s,\psi|m)] \geq -\log p(s|m).$$

Excluding unnecessary details for the purpose of this work, the expression represents a Bayesian approach that measure the difference between the cognitive load (energy) E_q to gain a knowledge of a set p with a set of unknown states q. H stands thus as an entropy measure. Higher is the free energy F, lower is the likelihood and therefore the accurate representation of the reality. Because p and q (term D is called divergence) are conditional states, a large number of observation does not necessarily implies a lower free energy. It is a powerful tool and its validity has been proven in many fields.
Curiously, this equation formally resembles the Minimal Potential Energy for Stability Analysis of solids. By minimizing, in fact, the work of the internal and external states the equilibrium configuration is obtained. Because in this case the two sates are mutual by the force-displacement duplicity, there is no divergence term and the solution is unique. Therefore, in the case of external forces applied to a MB equipped with an Intelligence capable to mutually react, the MB itself assume the minimum energy surface configuration, implying that the scope of the intelligence is the structural integrity. Friston brilliantly describe how the FEP is directly connected with the emergence of life and its fundamental role of resisting [23]. As previously stated, the role of a MB is to separate the intelligence from the rest, therefore a fracture in MB would translate into a destruction of the agent. If we imagine a drop of ink in a water glass, it would immediately dissolve through the act of random fluctuations of the fluid after few seconds. If anyway, the drop could possess an intelligence apt to sense the random fluctuations and respond in order to maintain a structural integrity, it would pulse and look alive to the eye of an external observer, and doted with a metabolism proportional to the resisting work (Figure 1). Capitalizing on this example, we are interested to know if the drop can learn how to react towards external fluctuations by feeding the

intelligence with a numbered of trained solutions. Moreover, creating axiomatic constraints on the same intelligence if the same solutions can be achieved in an intuition-like scheme.

(a) (b)

Fig. 1: a) drop of ink b) advance dissolving [23]

3 CauShee module

CauShee (Computer automated Structural analysis solver) is one of the research project developed during the FORSEES MSCA Action, and it's based on the approach described above. The system uses CV to solve simple structural arrangements as the one in Figure 2. A CNN based on a standard ResNet50 has been trained to classify loading type (red), restraints (yellow) and geometries (cyan). The same procedure has been used to train the CNN for internal action drawings. Pix2pix layers have been added to have an interpolating drawing result. In Figure 3, the bending moment is shown in red. At the same time, an intuitive-like solution has been implemented using the FEP. In details, it is possible to reduce the system entropy by discarding all the non-admissible solution by the compatibility equations, from all the possible system state. In fact, we can compute the disorder (D) by

$$D = \sum (p_i - P_{P_Y}), \tag{2}$$

with

$$P_Y = E(\omega_{i-1}), \tag{3}$$

where E is the expected value of the compatible solutions P_Y. Order metric O is instead

$$O = 1 - \frac{C_D}{C_I} \tag{4}$$

in which C_I is the number of indeterminate solution. Therefore, by imposing for example that solutions with non null bending moment at the pin extremity are determinate and not to be computed, the entropy of the system decreases as the free energy. A quantize distribution of possible internal actions points $p_x = p(x_1, x_2, ..., x_n)$ has been considered, using Shannon formula

$$H(x) = -\sum p_i \log p_i. \tag{5}$$

In Figure 3 the green line represents the solution of this approach.

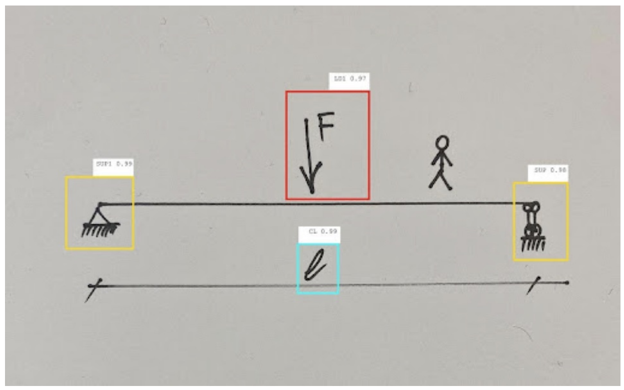

Fig. 2: Structural arrangement data classification

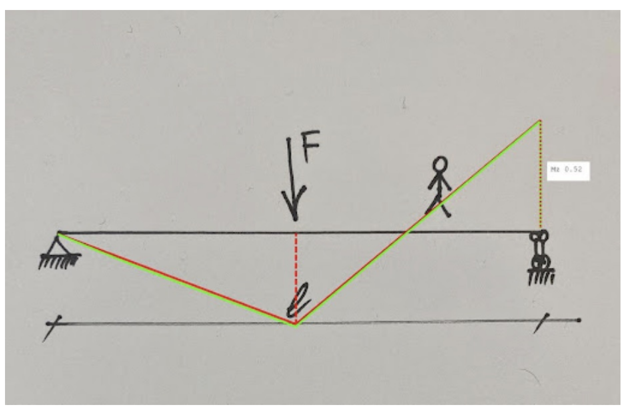

Fig. 3: Bending moment solution with CNN (red) and intuitive FEP approach (green).

4 Vulneracities module

In this section the results of another research module of the FORSEES MSCA Action are presented. Vulneracities is a project dedicated to assess seismic vulnerability of urban morphologies through visual analysis. The scientific base model is the FEMA Rapid Visual Screening (RSV) implemented more than 30 years ago for large scenario inspection [24]. Developed for the US building stock, it consists on a 2 level survey that identifies the building structural typology (among 16 classes) and assigns a risk basic score. This score can be subjected to modifiers with the presence/absence of structural peculiarities. For example, the soft-story can knock-down the basic score of a concrete building by half. Capitalizing on the CV potential, a DCNN (Deep Convolutional Neural Network) has been trained to perform this classification task. A database of 5m buildings has been used extracting facades from Google Street View API. For details see [25]. In Figure 4 the activation layer maps of a Densenet-201 have been reported. The first row represent the classification performed using the classical CV training, while the bottom row has been obtained by the use of the FEP approach. In this case, the reduction of the entropy has been obtained by imposing some causal eclusion, i.e. the presence of bow window automatically excludes the structural typologies that are not wooden structures bases (D) or masonry (C). Both the network rightfully predicted the class D, but the intuitive scheme used the window as discriminant, as a deployed engineer would do.
The same results are presented in Figure 5. In this case the building typology to classify was a masonry wall arrangement (C). Again, it is possible to note that the intuitive solution detected succesfully the building using the peculiarity of the window profile.

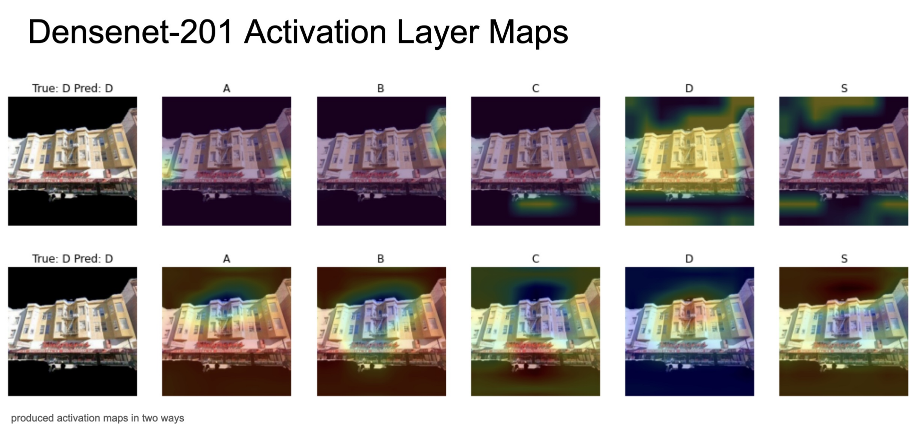

Fig. 4: Activation map for a five building typology classification. First row is the classical ML approach, while bottom row is for the intuitive solution.

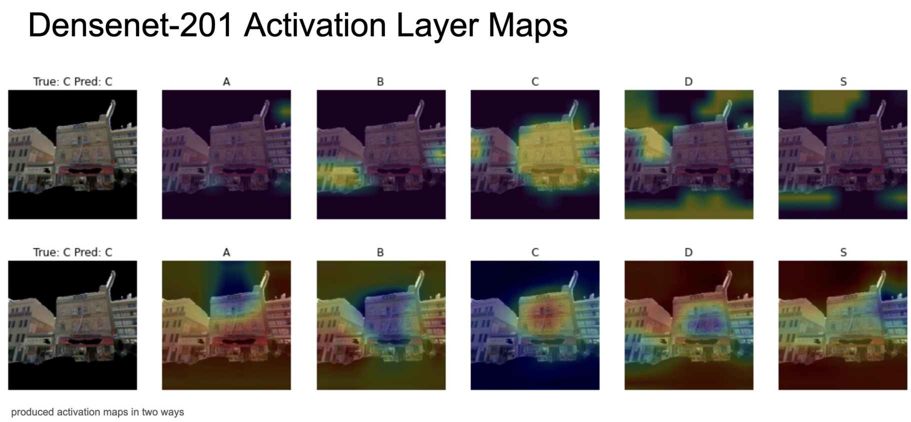

Fig. 5: Activation map for a five building typology classification. First row is the classical ML approach, while bottom row is for the intuitive solution.

5 Conclusion

The paper presents the use of axiomatic schemes for structural analysis tasks in the modern use of Computer Vision and visual analysis. The Free Energy Principle has been use to frame an intuition term inside the Bayesan approach. By acting on the entropy term, it is possible to reduce the number of open solution, through the introduction of idiosyncratic constructs. Although the model is at germinal state and requires more validation, it seems to correctly grasps both the theoretical and practice-based boundaries that experience in structural analysis has consolidated.

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