

In memory of our friend Alfredo

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This special session is dedicated to Alfredo Petrosino who unfortunately passed away prematurely few weeks ago

It is not easy for me commemorating a friend. Many of you had known Alfredo and I would like to try with you retracing our memories of him

Alfredo was a friend, colleague and mentor full of enthusiasm, tenacity and talent

I would like to remember that also in this last months, he has been morally present until the end of his days, hiding his illness and difficulties

# Appointments held

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- ❑ 1989

- ❑ M.Sc. in Computer Science at the University of Salerno, Supervisor E. R. Caianiello, Neural Networks pioneer

- ❑ 1989 – 1994

- ❑ Fellow researcher at the National Research Council (CNR)

- ❑ 1995

- ❑ joined the International Institute for Advanced Scientific Studies (IIASS)

- ❑ 1996 to 2000

- ❑ joined the National Institute for Physics of Matter (INFM) as researcher

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Alfredo was very proud of having been a collaborator of Caianello. I remember that in his office he had a poster with a picture of him

The collaboration with the IIASS continued throughout his life. Here he met among others Prof. Maria Marinaro, Prof. Anna Esposito, Tina Nappi.

My first memory of Alfredo dates back to this last period. In 1998 I began to work on my laurea thesis at the University of Salerno and I also remember the participation to the first conferences, as the WIRN conference, together my supervisor Roberto Tagliaferri and in those occasions I met Alfredo

# Appointments held

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## ❑ 2000

- ❑ joined the National Research Council (CNR) as researcher

## ❑ 2003

- ❑ was Senior researcher at the National Research Council (CNR)

## ❑ 2005

- ❑ he moved to the University of Naples Parthenope as Associate Professor
- ❑ Responsible of Computer Vision & Pattern Recognition Laboratory, DiST, University of Naples Parthenope
  - ❑ Node of «Laboratorio Nazionale di Artificial Intelligence and Intelligent Systems» (AIIS), CINI

A decorative horizontal bar in a light gray color spans the top of the slide. A vertical bar of the same color is positioned on the left side, extending from the top to the bottom of the slide.

In that last period I started a more intensive collaboration with Alfredo

In 2006 Alfredo invited me to hold a seminar at the Parthenope University

I still remember the topics, Neuro-Fuzzy systems and Independent Component Analysis

In 2007 I joined his department as a researcher

# Appointments held

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## ❑ 2013

- ❑ Full Professor at the University of Naples Parthenope
- ❑ Coordinator of the M.Sc. in Applied Computer Science

## ❑ 2016

- ❑ Vice-president
  - ❑ IEEE Italy Section CIS Chapter

## ❑ 2018

- ❑ Vice-Rector of Information Technology at University of Naples Parthenope
- ❑ Supervisor iOS Foundation Program at University of Naples Parthenope
- ❑ Vice-President of Associazione Italiana per la ricerca in Computer Vision, Pattern Recognition e Machine Learning (CVPL-ex-GIRPR)

# Courses held

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- ❑ He taught courses on Operating Systems, Image Processing/Computer Vision and Machine Learning
  - ❑ 1991-2006, University of Salerno
  - ❑ 1997-1998, University of Siena
  - ❑ 1999-2006, University of Naples Federico II
  - ❑ 2001-2019, University of Naples Parthenope
- ❑ Book
  - ❑ Sistemi Operativi: un approccio basato su concetti, McGraw-Hill, 2009



# Editorial activities

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- ❑ Editorial board
  - ❑ Information Sciences
  - ❑ Pattern Recognition Letters
  - ❑ IET Image Processing journals
  
- ❑ co-editor of special issues
  - ❑ IEEE SMC
  - ❑ Image and Vision Computing
  - ❑ Parallel Computing

# Research activities

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## ❑ Organizer of

- ❑ 17th International Conference on Image Analysis and Processing, 2013
- ❑ Workshop on Formal Language and Automata, 2016
- ❑ Computer Vision, Pattern Recognition and Machine Learning Conference (CVPL), 2018
- ❑ IAPR Summer School on Machine and Vision Intelligence (VISMAC), 2018
- ❑ 12th International Conference on Internet and Distributed Computing Systems (IDCS), 2019
- ❑ Workshop on Fuzzy Logic and Applications (WILF) about computational intelligence topics since 1995



WILF has always been a reference conference for me

I have a good memory of the conference WILF 2005 in Crema, where with Alfredo and Prof. Michele Ceccarelli spent a wonderful evening talking about research

# Research interests

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- ❑ His research interests covered a broad spectrum of issues related to
  - ❑ Computational Intelligence
  - ❑ Intelligent Systems
  - ❑ Machine Perception and Sensors
  - ❑ Pattern Analysis and Recognition
  - ❑ Neural Networks and Machine Learning methods
  - ❑ Image Processing and Analysis
  - ❑ Computer Vision

# Research interests

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- ❑ The mainstreams of the research in collaboration with other components of the CVPRLab
  - ❑ Pattern Recognition
    - ❑ Neural Networks
    - ❑ Markov Random Fields
    - ❑ Neuro-Fuzzy systems
    - ❑ Rough Sets
    - ❑ Kernel Methods
    - ❑ Learning and model selection
  - ❑ Applicative issues
    - ❑ shape classification
    - ❑ event detection and classification
    - ❑ clustering
    - ❑ tracking
    - ❑ video surveillance

# Research interests

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- ❑ Computer vision
  - ❑ image analysis
  - ❑ multiresolution
  - ❑ object recognition
  - ❑ soft computing in image analysis
  - ❑ attentive vision mechanisms with applications to video surveillance
  - ❑ medical imaging
  - ❑ multimedia data treatment

## ORIGINAL CONTRIBUTION

### Neural Associative Memories With Minimum Connectivity

EDUARDO R. CAIANIELLO AND ANTONELLA DE BENEDICTIS\*

Università degli Studi di Salerno

ALFREDO PETROSINO

Istituto di Ricerca sui Sistemi Informatici Paralleli (IRSIP)-C.N.R.

AND

ROBERTO TAGLIAFERRI

Università degli Studi di Salerno

(Received 2 May 1991; revised and accepted 25 October 1991)

**Abstract**—In this paper a binary associative network model with minimal number of connections is examined and its microscopic dynamics exactly studied. The knowledge of its time behavior allows us to determine a learning rule which realizes a one-step recalling associative memory. Its storage capacity is also analyzed with randomly distributed patterns and is proved to be  $O(\log n)$  in the worst case,  $n$  being the number of neurons and connections, but to increase considerably when the patterns to be memorized are correlated. Spurious states are also investigated.

**Keywords**—Neural networks, Connectivity, Associative memory, Microscopic dynamics, Learning, Storage capacity.

#### 1. INTRODUCTION

In the last decade, in particular since Hopfield (1982) proposed the spin glass analogy for neural nets, many papers were written about associative memory models and their capacities (Amari, 1990; Amari & Maginu, 1988; Amit, Gutfreud, & Sompolinsky, 1985; Gardner, 1988, 1989; McEliece, Posner, Rodemich, & Venkatesh, 1987). A large number of results on this subject highlight the importance of information coding and of the number of active neurons in the net in determining the information and memory capacity of an associative memory. It is well known (Abbott, 1990; Palm, 1988) that the sparseness of the coupling coefficient matrix does not change the performance of an associative memory when this is used in specific real applications; a result which permits to save memory space and reduce the recall time of patterns.

**Acknowledgements:** We thank Professor M. Marinaro for helpful discussions and suggestions. This work was supported in part by C.N.R., Progetto Finalizzato "Sistemi Informatici e Calcolo Parallelo," by MPI 40% and by I.I.A.S.S.

Requests for reprints should be sent to Professor Eduardo R. Caianiello, Dipartimento di Fisica Teorica e S.M.S.A., Università degli Studi di Salerno, I-84081 Baronissi (Salerno), Italy.

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The present paper gives a mathematical analysis of an associative memory model based on a neural net with minimal connectivity among neurons (i.e., a neural net with  $n$  neurons and  $n$  connections). This helps to clarify some open problems connected to information and memory capacities.

More specifically, Section 2 is dedicated to define the model under consideration; some basic properties of this model, like its temporal evolution, are discussed in Section 3. Section 4 reports a study of the behavior of this model as associative memory in absence of cycles, called by us Instantaneous Associative Memory. In Section 5 we provide an algorithm to memorize randomly distributed patterns, one at a time. Finally, Section 6 shows that the storage capacity of this model strongly depends on the structure of the random patterns selected for memorization. A discussion of the model closes the paper.

#### 2. THE NEURAL NETWORK MODEL

Let us consider a neural network of  $n$  neurons which evolves synchronously at discrete times. The network state is determined according to the rule (Caianiello, 1961, 1986):

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Alfredo authored several important works. I would like remembering some of the most known by scientific community

In this paper a binary associative network model with minimal number of connections is examined

This is one of the first scientific works I read in 1997 during the course on neural networks at the University of Salerno and I was very impressed by the methodological rigour



## Neural Recognition in a Pyramidal Structure

Virginio Cantoni and Alfredo Petrosino

**Abstract**—In recent years, there have been several proposals for the realization of models inspired to biological solutions for pattern recognition. In this work we propose a new approach, based on a hierarchical modular structure, to realize a system capable to learn by examples and recognize objects in digital images. The adopted techniques are based on multiresolution image analysis and neural networks. Performance on two different data sets and experimental findings on a single instruction multiple data (SIMD) machine are also reported.

**Index Terms**—Multiresolution, pyramidal architecture, shape recognition, single instruction multiple data (SIMD) parallel machine, structured neural network.

### I. INTRODUCTION

SEVERAL approaches are pursued, in the last years, in the field of image processing and recognition based on pyramidal structures (see, for instance, [6], [8], [11], [21], [30], [32], and [33]). Pyramids are compact, multiscale representations that produce good textural features for landscape characterization, providing also support of efficient coarse-to-fine search. On the contrary, neural networks are suitable for learning ill-defined relationships from noisy examples, including relationships between different data types. Efforts toward developing neural network/pyramid techniques for recognition purposes arose as a way to handle problems of scaling with input dimensionality. Indeed, as reported by Geman *et al.* [15], “important properties of patterns must be built-in or hard-wired, perhaps to be ... (tuned) ... later by experience, but not learned in any statistical meaningful way”.

The ideas reported in this and other related papers can be traced back to “biased models” for solving most meaningful practical problems, i.e., neural modeling is no longer focused exclusively on learning, but also on the identification of significant structure and weight constraints. This tries to reduce the number of free parameters to learn and consequently the complexity of learning. From the practical standpoint, this results in a less number of learning iterations, without strongly affecting the generalization capabilities of the network. Other possible ways consist of the application of statistical techniques, aimed to reduce the input dimensionality (and consequently the number of weights), like principal component analysis, independent component analysis, or pruning techniques to the weight space (see [19]).

Considerable interest has been gained by convolutional networks where each neuron is linked to a restricted number of neu-

rons through weight sharing. This efficiently reduces the model complexity and the number of weights of the network, with a consequent advantage in learning complexity when high-dimensional images are to be presented directly to the network instead of using explicit feature extraction and data reduction. Moreover, networks with local topology can more effectively be mapped to a locally connected parallel computer than fully connected feedforward networks. For example, Le Cun [25], [26] has proposed the use of receptive fields in feedforward nets, which result in special equality constraints on the weights. Fukushima [14] considered a combination of receptive fields and competitive learning to realize a multilayered network for recognizing handwritten digits, capable of extracting and classifying features. Applications of these models have been made in handwritten character and face recognition. Different convolutional networks, which have been demonstrated to discriminate more effectively between different classes of input, have been proposed in literature (see, for instance, [22], [27]). The use of more layers of receptive fields do not assure a successful classification of the features extracted in previous layers, while multilayer perceptrons perform better. Among others, Perantonis and Lisboa [29] have introduced a method for reducing the number of weights of a third-order network used for pattern recognition by imposing invariance under translation, rotation, and scaling.

From the standpoint of relationships between pyramids and networks, Bishof *et al.* [2] have compared neural networks and image pyramids, showing how a modified Hopfield network can be used for irregular decimation and examining the type of knowledge stored and the processing performed by pyramids and neural networks.

These and other papers report significant attempts to incorporate domain knowledge into neural networks (e.g., in terms of weight constraints). Since the incorporation of the domain knowledge turns out to be a complex task for neural networks, an alternative approach is to consider multiscale representations of input patterns, giving a regular structure to the network, without inserting *a priori* knowledge into the network. Moreover, but not less important, both neural networks and pyramids map well onto fast hardware for high-throughput applications. Some works have been developed along this research activity.

In particular, the pyramidal neural network reported by McQuoid [24] is arranged on four layers, one corresponding to the “retina” (or input image) and three layered neuronal areas; the neurons within each area are organized in columns of ensembles. The Area 1 is constructed from planes of ensembles, each aligned above one another, forming a number of ensemble columns. An ensemble consists of a  $5 \times 5$  grid of neurons, each connected to the retina area directly below the corresponding neuron, with the same set of weights. Since there is one column for each input neuron belonging to an input field of  $7 \times 7$  neurons, the weight sharing here allows the ensemble to realize

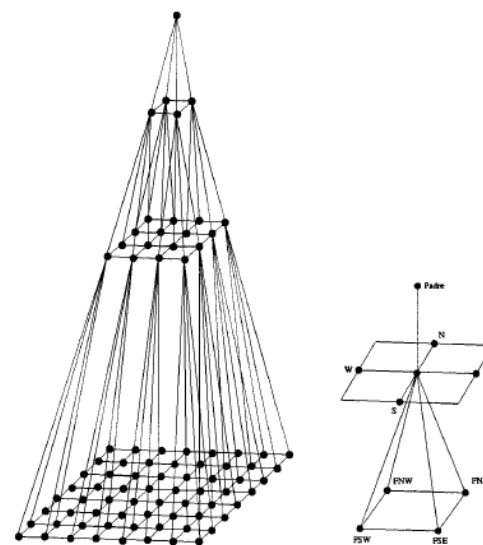


Fig. 6. (a) The pyramidal architecture and (b) the interlayer and intralayer connectivity of the processors.

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The model presented in this work is based on a hierarchical modular structure for realizing a system capable to learn by examples and recognize objects in digital images

The adopted techniques are based on multiresolution image analysis and neural networks

This work is still actual and mainly used by deep neural networks based approaches for object recognition in computer vision

## Encoding Nondeterministic Fuzzy Tree Automata Into Recursive Neural Networks

Marco Gori, *Fellow, IEEE*, and Alfredo Petrosino, *Member, IEEE*

**Abstract**—Fuzzy neural systems have been a subject of great interest in the last few years, due to their abilities to facilitate the exchange of information between symbolic and subsymbolic domains. However, the models in the literature are not able to deal with structured organization of information, that is typically required by symbolic processing. In many application domains, the patterns are not only structured, but a fuzziness degree is attached to each subsymbolic pattern primitive. The purpose of this paper is to show how recursive neural networks, properly conceived for dealing with structured information, can represent nondeterministic fuzzy frontier-to-root tree automata. Whereas available prior knowledge expressed in terms of fuzzy state transition rules are injected into a recursive network, unknown rules are supposed to be filled in by data-driven learning. We also prove the stability of the encoding algorithm, extending previous results on the injection of fuzzy finite-state dynamics in high-order recurrent networks.

**Index Terms**—Fuzzy neural networks, fuzzy systems, fuzzy tree automata, knowledge representation, recursive neural networks.

### I. INTRODUCTION

THE general tendency of merging fuzzy systems and neural networks appeared quite early in the development of fuzzy sets [22]. Bearing in mind an evident overlap in the architecture characteristic for fuzzy sets and neural networks, these two complementary technologies can produce an efficient synergy for the design of “intelligent” procedures. Several researchers have considered the possibility of integrating the advantages of fuzzy systems with those not less known of neural networks, giving rise to fuzzy neural networks (see [21] and [24] as representative sources to this regards). These kinds of studies are very interesting in all the application domains where the patterns are strongly correlated through structure and the processing is both numerical and symbolic, without discarding the component of structure which relates different portions of numerical data and the imprecise and incomplete nature of the data. First application perspectives are: automated reasoning and theorem proving [17], computational chemistry [2], [32], logo recognition [7], but other ones include medical and technical diagnoses, molecular biology, software engineering, geometrical and spatial reasoning, speech and natural processing and different applications of pattern recognition (see [10] for detailed considerations on these application domains).

For instance, let us consider problems of syntactic pattern recognition [11], [12]. Certain pattern classes contain objects,

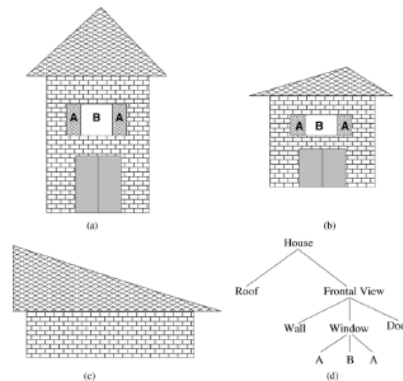


Fig. 1. Some examples of “houses” (a–c) and the tree structural representation (d). A real valued function  $\mu$  is attached to each vertex to express the degree of membership of the associated concept. As example, denoting with  $\text{triangle}_a$ ,  $\text{triangle}_b$ , and  $\text{triangle}_c$  the labels associated to the roof component of the trees, respectively, corresponding to the examples (a), (b), and (c), the membership values to the roof concept satisfy  $\mu_{\text{roof}}(\text{triangle}_a) > \mu_{\text{roof}}(\text{triangle}_b) > \mu_{\text{roof}}(\text{triangle}_c)$ .

such as geometric figures, with an identifiable hierarchical structure that can be described by a formal grammar. A basic set of pattern primitives is selected and forms the set of grammar terminals. Grammar productions are a list of allowable relations among the primitives, while the pattern class is the set of strings generated by the grammar or the equivalent automaton. When the indeterminacy is due to inherent vagueness, the imprecise nature of patterns could be handled by fuzzy languages; the fuzziness may lie in the definition of primitives or in the physical relations among them. Thus, the primitives become labels of fuzzy sets and the production rules of the grammar are weighed. Fuzzy languages have shown some promise in dealing with patterns which possess ill-defined (fuzzy) boundaries [26], [31], [33], [37], [39]. The patterns are not only structured (usually tree structured), but each pattern primitive has a subsymbolic nature and lastly a fuzziness degree is attached to it. From the bottom to the top the pattern evolves in structure; this leads to consider more refined pattern representations and description. A pattern may be also represented at various resolution levels by a graph of primitives and their relations, and a grammar, whose production rules describe the evolution of the object primitives at increasing resolution levels, is introduced [3], [5].

In Figs. 1 and 2, two examples are sketched.

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This is an important work for analysing structured data

This was one of the inspiring works for developing a classification methodology for structured data based on fuzzy rules, that I studied with Alfredo and Prof. Witold Pedrycz

## A Self-Organizing Approach to Background Subtraction for Visual Surveillance Applications

Lucia Maddalena and Alfredo Petrosino, *Senior Member, IEEE*

**Abstract**—Detection of moving objects in video streams is the first relevant step of information extraction in many computer vision applications. Aside from the intrinsic usefulness of being able to segment video streams into moving and background components, detecting moving objects provides a focus of attention for recognition, classification, and activity analysis, making these later steps more efficient. We propose an approach based on self organization through artificial neural networks, widely applied in human image processing systems and more generally in cognitive science. The proposed approach can handle scenes containing moving backgrounds, gradual illumination variations and camouflage, has no bootstrapping limitations, can include into the background model shadows cast by moving objects, and achieves robust detection for different types of videos taken with stationary cameras. We compare our method with other modeling techniques and report experimental results, both in terms of detection accuracy and in terms of processing speed, for color video sequences that represent typical situations critical for video surveillance systems.

**Index Terms**—Background subtraction, motion detection, neural network, self organization, visual surveillance.

### I. INTRODUCTION

VISUAL surveillance is a very active research area in computer vision thanks to the rapidly increasing number of surveillance cameras that leads to a strong demand for automatic processing methods for their output. The scientific challenge is to devise and implement automatic systems able to detect and track moving objects, and interpret their activities and behaviors. The need is strongly felt world-wide, not only by private companies, but also by governments and public institutions, with the aim of increasing people safety and services efficiency. Visual surveillance is indeed a key technology for fight against terrorism and crime, public safety (e.g., in transport networks, town centers, schools, and hospitals), and efficient management of transport networks and public facilities (e.g., traffic lights, railroad crossings) [1].

The main tasks in visual surveillance systems include motion detection, object classification, tracking, activity understanding,

and semantic description. Our focus here is on the detection phase of a general visual surveillance system using static cameras. The detection of moving objects in video streams is the first relevant step of information extraction in many computer vision applications. Aside from the intrinsic usefulness of being able to segment video streams into foreground and background components, detecting moving objects provides a focus of attention for recognition, classification, and activity analysis, making these later steps more efficient, since only moving pixels need be considered [2].

The usual approach to moving object detection is through background subtraction, that consists in maintaining an up-to-date model of the background and detecting moving objects as those that deviate from such a model. Compared to other approaches, such as optical flow (e.g., [3]), this approach is computationally affordable for real-time applications. The main problem is its sensitivity to dynamic scene changes, and the consequent need for the background model adaptation via background maintenance. Such problem is known to be significant and difficult [4]. Some of the well-known issues in background maintenance, that will be specifically addressed in the sequel, include:

- *light changes*: the background model should adapt to gradual illumination changes;
- *moving background*: the background model should include changing background that is not of interest for visual surveillance, such as waving trees;
- *cast shadows*: the background model should include the shadow cast by moving objects that apparently behaves itself moving, in order to have a more accurate detection of the moving objects shape;
- *bootstrapping*: the background model should be properly set up even in the absence of a complete and static (free of moving objects) training set at the beginning of the sequence;
- *camouflage*: moving objects should be detected even if their chromatic features are similar to those of the background model.

Our approach to moving object detection is based on the background model automatically generated by a self-organizing method without prior knowledge about the involved patterns. The idea consists in adopting biologically inspired methods for moving object detection, where visual attention mechanisms are used to help detecting objects that keep the user attention in accordance with a set of predefined features, such as gray level, motion, and shape features. It will be shown, by qualitative and quantitative results, that our adaptive model, extending [5], can cope with all the above mentioned issues for background

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Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

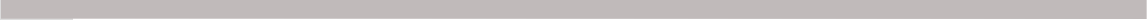
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This work has had a great impact in the computer vision scientific community

It is still used for many challenges on benchmarks data

Many extensions are proposed also in this last years

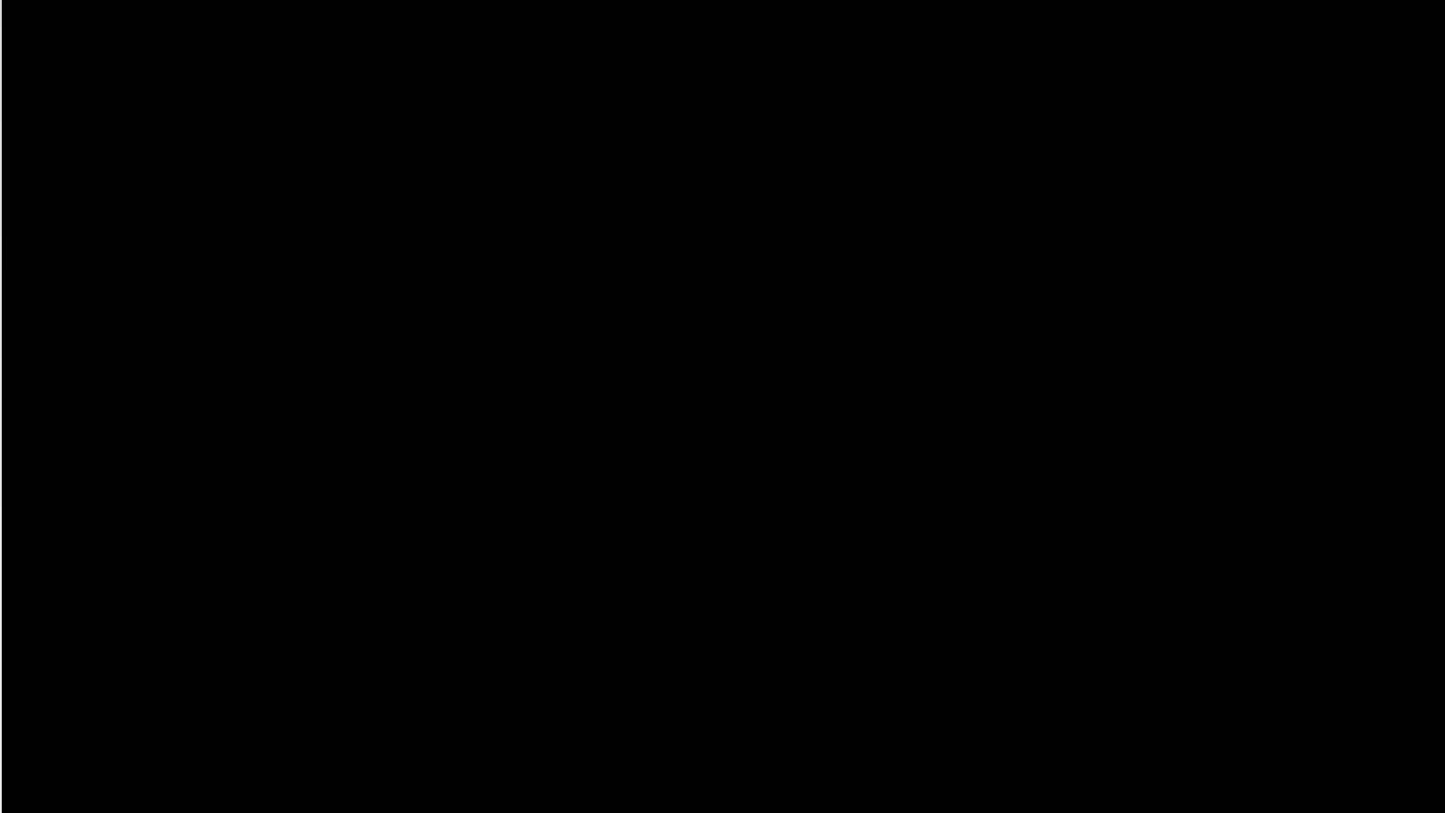


In recent years Alfredo has devoted much of his time for managing the Apple Foundation

I would like to present you a brief presentation of Alfredo at the Addademy

# Interview at Apple Foundation

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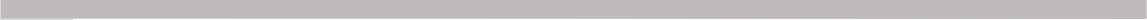






We will always remember you as a friend,  
colleague and mentor full of enthusiasm,  
tenacity and talent.

A hug.  
Bye Alfredo



I would like to thank Alfredo for everything he taught us and above all for how to deal things with tenacity

My strong hug goes to the family