# A Review on Humanized Computational Intelligence

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**Abstract**

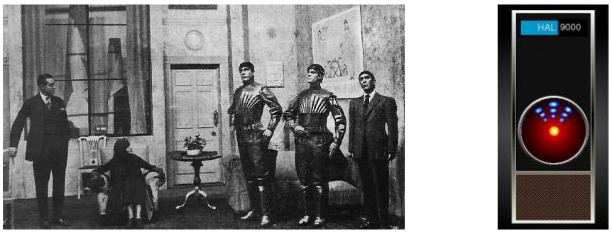
Computational Intelligence (CI) has three main foundations: Neural Networks, Evolutionary Computation (EC) and Fuzzy Systems (FS). Collaborating systems based on these models have been built and installed in prototypes and successful consumer products. However, creativity still is a main human task, in great part due to the presence of subjective values and psychological / emotional responses in the evaluation of the created objects. In this context the Interactive Evolutionary Computation (IEC), a paradigm in which humans directly intervene in fitness evaluation, is a new direction for CI research. Art, education and engineering are some examples of IEC application domains.

# 1. Introduction

Webster's New Collegiate Dictionary defines intelligence as "the ability to learn or understand or to deal with new or trying situations, the skilled use of reason and the ability to apply knowledge to manipulate one's environment or to think abstractly as measured by objective criteria (or tests)"[1].

The idea of incorporating intelligence into “machines” is not new. Some paradigmatic examples come from the Science Fiction field: in 1921, Karel Capek, Czech writer, introduced the term *robot* in the play *R.U.R. (Rossum's Universal Robots)* to describe intelligent biological machines (they were assembled, not born or grown) that revolted against their human masters (fig. 1A); and in 1968 the film "2001: A Space Odyssey", directed by Stanley Kubrick, from Arthur C. Clarkes' book, presented HAL 9000, the humanized computer whose name is a reminder of the giant company, IBM (fig.1B).

Meanwhile and in the real world, in 1928 John von Neumann introduced the *minimax theorem*, which is still used as a basis for game-playing programs. In 1950 the so called father of Artificial Intelligence (AI), Allan Turing, proposed the Turing Test to recognize machine intelligence: according to Turing, intelligent behavior is the capability of acting as a human being in any cognitive task, in a degree enough to fool the interrogator [15].




A B

**Fig. 1.** A) R.U.R - Rossum's Universal Robots - A scene of the play (Karel Capek) B) HAL 9000, the computer of "2001 - A Space Odissey"

However, the term AI was proposed by John McCarty a few years later at the Dartmouth workshop of 1956 where Marvin Minsky, Claude Shannon and others were also present. According to a statement of the Dartmouth conference participants, "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it".

Perhaps inspired by this principle, in 1956 Newell and Simon created the General Problem Solver (GPS), an algorithm virtually capable of solving any problem. By this time AI was looking for general solutions rather than concentrating on specific fields and knowledge based systems.

By the 50s the AI community was the first large established scientific community. The evolution of AI is summarized by Mackworth [2]: "In AI's youth, we worked hard to establish our paradigm by vigorously attacking and excluding apparent pretenders to the throne of intelligence, pretenders such as pattern recognition, behaviorism, neural networks, and even probability theory. Now that we are established, such ideological purity is no longer a concern".

In fact, in 1958 Frank Rosenblatt introduced the perceptron; an active research program into this paradigm was carried out throughout the 60s, then almost suspended and later resumed. Genetic algorithms became popular through the work of John Holland in the early 1970s, particularly by [17]. Fuzzy Logic was born by the hand of Lofti A. Zadeh in 1965 [16]. Together, these three fields are the foundations of Computational Intelligence (CI).

According to IEEE Computational Intelligence Society, CI comprises four main areas: Evolutionary Computation (EC) (Genetic Algorithms (GA) and Genetic Programming (GP)), Fuzzy Systems (FS), Neural Networks (NN) and Swarm Intelligence (SI). Furthermore CI is closely related to Fractals and Chaos Theory.

EC and SI are biological inspired algorithms. The former uses an iterative progress such as the development of a population by means of crossover and mutation operations; some individuals are then selected in a guided random search trying to achieve a desired goal. The last is inspired by the behavior of individual agents such as birds, ants or bees, and their interactions; from these interactions a global intelligent behavior emerges that converges to a desired goal. In both cases the fitting of the populations into the target is measured by a *fitness function*. NNs mimic the behavior of brain cells and their links. The resulting structures are able to learn by example, so exhibiting an intelligent behavior and learning as humans do. Last but not least in the context of this paper, Fuzzy Sets and Fuzzy Logic define membership functions and continuous logic degrees of *true* that support the mathematical translation of linguistic terms thus allowing "computing with words" [18]. Fuzzy Logic control systems, for instance, "tune" as humans do: "if high, decrease it"; "if low, increase it". They work in a humanized way.

## 2. Humanized Computational Intelligence

In the last two decades, EC, NN and FS technologies have been widely used in prototypes as well as in cooperative models integrated into successful consumer products. Some of these systems deal with particular human capabilities. Kismet, for instance, is a robot developed at Massachusetts Institute of Technology (MIT) in the late 90's and now residing at the MIT Museum that interacts with humans showing and perceiving emotions (fig.2). However, "the interaction between the caretaker and the robot is purely social, much like how a mother interacts with her infant" [19]. Kismet resides essentially on the concept of affective computing, i.e. recognition, interpretation and processing of human emotions. Kismet follows the traditional approach of modeling human capabilities and installing them into the system.

The term Humanized Computational Intelligence (HCI) refers to a different concept: here the human contribution is directly embedded into a CI based system acting as a "black box". The human contribution is an active piece of the system.

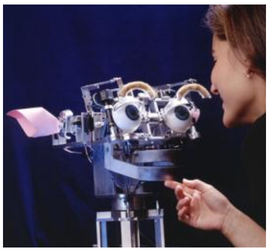


**Fig. 2.** Kismet interacting with Cynthia Breazeal (MIT)

For Takagi [6] one of the research directions on computational intelligence at the beginning of the 21st century is HCI. Imagine consumer robots whose market is expanding in Japan now: “cute”, “interesting”, or other subjective keyword is much more important for the robot consumer than efficiency measures used for the evaluation of the industrial ones. “Humans tend to fear an approaching robot arm”. The objective of a research may be to minimize this fear by determining the best path and speed of the robot arm. “This type of approach became important for care robots, pet robots or other consumer robots where friendliness is required rather than efficiency”.

For this kind of problem a subjective evaluation is needed. The same applies to creative tasks in the domain of music, plastic arts and writing. As the goal of the fitness function of EC is exactly “evaluation”, EC is specially tailored to support HCI, giving rise to the concept of Interactive Evolutionary Computation (IEC). In IEC the evolutionary process is controlled by humans directly. In another words, the fitness function of IEC is represented by the opinion of a human being.

## 3. Interactive Evolutionary Computation

The idea of using human knowledge or intuition as part of an optimization process appeared in [4]. This subjective optimization approach means that, instead of defining a mathematical cost function, the human user directly evaluates the potential solutions and makes a decision about which solutions are good and which are bad [5]. However, most of the classical optimization methods, which work by improving a single solution step by step, are not suited for this technique. On the other hand EAs and other population based optimization procedures are well suited for subjective optimization:

EAs are optimization methods that use a computational model of natural selection. EAs have proved particularly successful in problems that are difficult to formalize mathematically and which are, therefore, not conducive to classical analysis based engineering tools. EAs work with a population of potential solutions where each individual represents a particular solution, generally in some form of genetic code.

Each individual is called genotype. The fitness value of each individual expresses how good it is, for solving the problem, the solution it represents. The better the solution, the higher the value of the fitness function. The external appearance of a genotype is called phenotype.

The key of EAs is that the fitness also influences how successfully each individual will be for propagating its genes (its code) to subsequent generations, as the intervention of stochastic operators in the selection process tends to benefit the more suited ones. As this description suggests, this approach is ideal for subjective optimization since the human user can directly evaluate the fitness of the solutions by ordering the best individuals or by selecting the best ones (fig. 3).

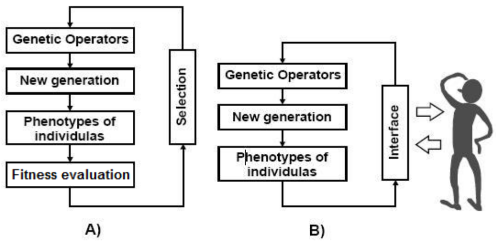



**Fig. 3.** A) Evolutionary Algorithm B) Interactive Evolutionary Algorithm [5]

This approach became known as Interactive Evolutionary Computation (IEC) [6], a form of HCI. One of the main issues in this context is human-computer interaction (HCInt) as the evaluation process must be conducted in a comfortable and easy-to-use way.

## 3.1 IEC Basics

Among other characteristics, an interactive fitness evaluation is characterized by:

1. Phenotype evaluation: human evaluation requires that each solution be "shown as it is". In other words, each genotype must be transformed into its corresponding phenotype before the human evaluation takes place. For instance, a melody must be heard by the user; it does not make sense to evaluate it by looking to its genotype, as its beauty will not have the desired emotional impact. On the contrary, in traditional GAs the fitness evaluation is made on the genotype.
2. User's fatigue: in IEC humans are competing with tireless computers. So, user's fatigue is a major problem. Some approaches follow:
    a. Small population: in classical GAs the population may vary from

some to hundreds or thousands of individuals. The evaluation of such a number of items would be extremely tedious for humans. So, in IEC the populations are kept small or the individuals chosen for interactive evaluation are only a few. On the contrary, in traditional GAs the fitness evaluation is made for every individual.

b. Small number of iterations: in classical GAs the number of iterations may be very high. In IEC this is no longer possible due to the user's fatigue. So, in IEC convergence must be quick and effective.

c. Possibility of worst exclusion: the interactive evaluation may allow the user to immediately exclude some individuals due to their evident distance to the goal. On the contrary, in traditional GAs some worst solutions may be chosen to be kept in order to maintain diversity (genetic material).

Phenotype evaluation:

In IEC a user must see or hear the system outputs. The goal of the system is to optimize these outputs according to the user's preferences. So, IEC is a technology that combines aesthetical preferences, psychology, intuition and emotion. In this sense IEC may be considered a form of Kansei engineering [6].

Kansei engineering [21, 22], also called "sensory engineering" or "emotional usability", is a method for identifying what sensorial features of a product influence user's preferences by eliciting subjective responses, and then designing a product with such characteristics. In order to perform Kansei engineering one starts with a set of distinct products capable of determining different emotional responses. These responses can be evaluated by using bipolar attributes such as simple *versus* complex or white *versus* black, placed on a line. The human judgers are asked to place a mark on this line according to the classification they give to each product in face of the opposite attributes under evaluation. In consequence, products can be designed to evocate the desired emotional response; one may fall in love with a car, or feel that a robot is cute. Such techniques have been used in the design of Mazda MX5 - one the top selling coupes in the world - and by Sharp that saw its market share increase 8 times after the introduction of an LCD display in its video cameras, instead of the traditional ocular [20].

Clearly, in the phenotype evaluation field, HCInt plays an important role. This subject will be discussed in section 3.2.

Reduced population and number of iterations [6, 27]:

The differential thresholds of human perception establish the minimal amounts by which two stimuli of the same kind can be recognized as different from each other. Therefore, grey scales, colors and sound frequencies must be distinct enough to be differently classified by human judgers. This, allied to the necessity of reducing the number of examples to judge in order to avoid user's fatigue, suggests the discretization of system outputs, if and when possible. By reducing the number of examples this technique also helps user's memory that can be hardly requested from iteration to iteration.

The reduction of the number of examples to analyze can also be accomplished by predicting the fitness value of each individual. In this approach the GA can process a population of "normal" size (200 individuals, for instance) but only shows the phenotypes corresponding to genotypes that are predicted to have a high fitness value (10 individuals, for instance). NN, Euclidean distance / clustering [26, 27] and rule based techniques have already been tried with more or less success.

Finally, if the user finds a certain characteristic of an individual to be particularly satisfactory, the system may provide a means to "freeze" the genes associated with that characteristic, preventing the GA to destruct them in future iterations by eventual recombination [24, 27].

### 3.2 Human-Computer Interaction

Research in HCInt has changed the computer world. One example is the "Microsoft Windows interface, which is based on the Macintosh, which is based on work at Xerox PARC, which in turn is based on early research at the Stanford Research Laboratory and at the Massachusetts Institute of Technology" [23]. The mouse, hypertext, virtual reality and natural language processing are examples of other human-computer interaction systems that modified the way people communicate with computers.

As already mentioned this is an important issue in IEC. However, some particular problems arise in this area. For example, music can not be compressed in time. In this case, methods for reducing user's fatigue include the usage of various interchangeable sound sources, the possibility of reproducing older individuals to reduce user's memory effort and optimizing the design of the interface. For movies, simultaneous evaluation can be achieved for a small number of them. Images can be evaluated simultaneously since their number will be kept small; the interface should allow some interactivity in order to show individuals obtained in previous generations for comparison purposes.

## 4. Applications

There is a history of research related to interactive evolutionary computing which, in the main, relates to partial or complete human evaluation of the fitness of solutions generated by evolutionary search. In general, this approach was introduced where quantitative evaluation was difficult if not impossible to achieve.

Application examples include graphic arts and animation [8, 9]; automotive design [10]; food engineering [11] and database retrieval [12]. Such applications rely upon a human-centered, subjective evaluation of the fitness of a particular design, image, taste or any other aspect, as opposed to an evaluation developed from some analytic model.

Also, Hideyuki Takagi as categorize interactive evolutionary computation application fields into three categories: artistic applications, engineering applications and education, edutainment, and therapy [7].

Artistic applications include music, art, design and computational creativity. Graphic art and computer graphics animation, 3D computer graphics lighting design, music, editorial design, industrial design and face image generation are examples of more specific IEC artistic applications.

In some real-life optimization problems and in engineering problems, the objectives are often non-commensurable and are explicitly/mathematically not available. Hence, IEC can effectively handle these problems. IEC includes speech processing, hearing aids fitting, virtual reality, database retrieval, data mining, image processing, control and robotics, internet, food industry and geophysics.

Edutainment, an acronym for educational entertainment or entertainment-education, is a form of entertainment designed to educate as well as to amuse. Edutainment typically seeks to instruct or socialize its audience by embedding lessons in some familiar form of entertainment: television programs, computer and video games, films, music, websites, multimedia software, etc. Examples might be guided nature tours that entertain while educating participants on animal life and habitats, or a video game that teaches children conflict resolution skills. Examples of IEC application in education, edutainment and therapy consist on art education, writing education, games and therapy and social system [7].

Another type of IEC application is the measurement of human characteristics. Since IEC is an optimization method based on human subjective evaluation, it is possible to measure the evaluation characteristics or mental conditions of an IEC user by analyzing the outputs from the target system optimized by the user.

Likewise, research in this area includes topics that try to reduce IEC user fatigue [16]. As exposed, several approaches have been tried such as improving input/output interface, accelerating EC search, allowing human intervention into EC search, estimating human evaluations and others.

## 4.1. Art

### *4.1.1. Plastic Arts*

Galápagos is an interactive Darwinian evolution of virtual "organisms". Twelve computers simulate the growth and behaviors of a population of abstract animated forms and display them on twelve screens arranged in an arc, as shown in figure 4. The viewers participate in this exhibit by selecting which organisms they find most aesthetically interesting and standing on step sensors in front of those displays. The selected organisms survive, mate, mutate and reproduce. Those not selected are removed, and their computers are inhabited by new offspring from the survivors. The offspring are copies and combinations of their parents, but their genes are altered by random mutations. Sometimes a mutation is favorable, the new organism is more interesting than its ancestors, and is then selected by the viewers. As this evolutionary cycle of reproduction and selection continues, more and more interesting organisms can emerge.

Since the genetic codes and complexity of the results are managed by the computer, the results are not constrained by the limits of human design ability or understanding.

**Fig. 4.** Galápagos: interactive media installation that allows visitors to "evolve" 3D animated forms [13]

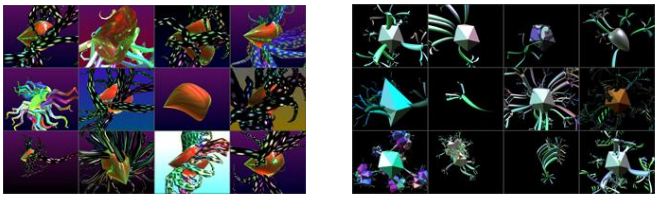


**Fig. 5.** Both images above show a "parent" in the upper left corner, and the remaining eleven are "offspring" from that parent. Mutations cause various differences between the offspring and their parents [13]

### 4.1.2. Music

CONGA is a multi-level interactive system that combines genetic algorithms with genetic programming to generate drum machine parts, developed by Tokui and Iba [15]. The paper focuses on rhythmic composition and besides the combination of two evolutionary algorithms, also uses a NN to learn user criteria so mixing interactive evolutionary computation with prediction of the fitness value.

Fig. 4 presents an overview of the system, which is based on MIDI - Musical Instruments Digital Interface - specification. The GA and GP populations are displayed as grids on windows respectively. Each cell of the grid is associated with an individual in the correspondent population. In this way, a user can listen to any individual by clicking the corresponding cells and assign a fitness value.

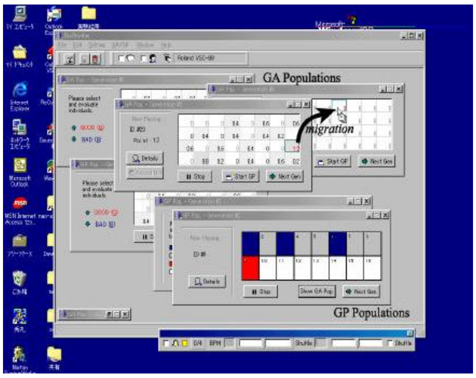



**Fig. 4.** The CONGA system [15]

In what concerns to the system architecture (fig. 5), the genetic representation contains two populations. These are: 1) a population of GA individuals, which represent short musical phrases; 2) a population of GP individuals, which represent how these short patterns are arranged in the time line. The alternation of generations occurs in these two populations based on the user's given fitness values.

The flexibility of the system was enhanced by introducing user-defined parameters. Users can set the population sizes, input the length of generated rhythm patterns and select timbres for composition. Users also can set "swing rate" of the rhythms. These features contribute to generating much more musical phrases. Besides this, the system can be synchronized with other MIDI sequencers.

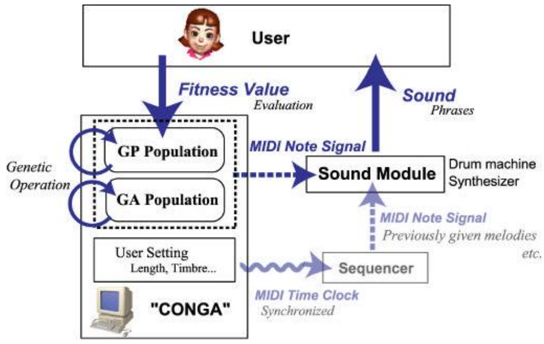



**Fig. 5.** The CONGA architecture [15]

## 4.2. Engineering

### *4.2.1. Design of Micro-electromechanical Systems (MEMS)*

MEMS, also known as micro-machines, are electromechanical mechanisms and transducers created using Integrated Circuits micro fabrication techniques. This IEC application refers to the development of resonating mass structure sensors, which are a simple MEMS example that can be extended to the design of MEMS-based RF filters or inertial sensors.

In the case of MEMS simulation, tractable simulation tools cannot predict the sensitivity of a design to fabrication uncertainty or/and do not include the effects of certain design features on performance. A study presented in [29] shows that these sensitivities can dramatically affect the quality of the solutions generated. Many of these potential problems are clearly visible to a human user visually observing the design layout, but they would be difficult, if not impossible, to mathematically model and simulate in software and incorporate into a flexible MEMS synthesis program. Therefore, Kamalian [28] developed an IEC based MEMS design tool to allow the inclusion of this human knowledge.

In this tool, a human evaluates each individual in each generation based on the layout as well as the performance prediction by a simulator tool. If the human detects bad design features the solution is scored negatively; on the opposite, if good features are detected, the human chooses to give a 'stay of execution' to the design, meaning that these features will be allowed to propagate to future generations. In summary, human can chose to give either a promote (positive) or demote (negative) reaction to each design presented, as shown in fig. 6.

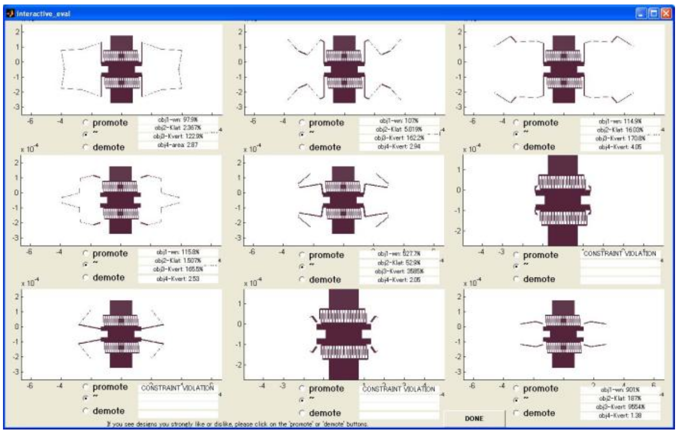



**Fig. 6.** User interface of IEC MEMS synthesis tool [28]

### *4.2.2. IEC lighting design support*

The goal of this application is the optimization of coordinates, light strengths and types of light of three lights in a 3D space to create the lighting impression matching with the given design concept. Fig. 7 shows design works of a same armature obtained with IEC (upper in fig. 7) and by hand (lower in fig. 7).

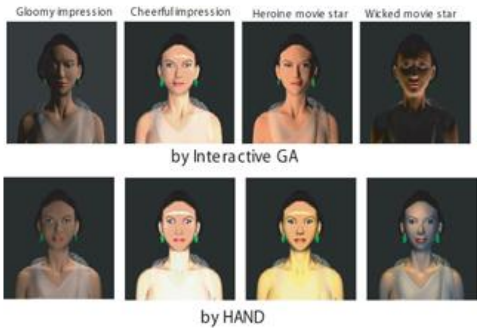



**Fig. 7.** IEC lighting design support [7]

## 4.3. Education, Edutainment and Therapy

### *4.3.1. Education: IEC-based Educational System*

The application presented in this sub-section is a 3-D Computer Graphics (CG) shape design support [30, 6], as shown in fig. 8. A rough 3-D shape is sketched by combining hyper-elliptical functions, while IEC changes the shape by changing the coefficients of the functions based on user's image in mind. This system allows anyone to realize CG images without CG skill. Also, this tool is directed for education, since it develops an artistic sense, rather than an artistic skill such as sketching and sculpting, allowing relatively unskilled art students to refine their artistic abilities.


**Fig. 8.** IEC-based 3-D CG System for Art Education [30]

### *4.3.2. Edutainment: The Artificial Painter*

The Artificial Painter is an application based on Artificial Neural Networks (ANN) and GA's with interactive fitness evaluation (although it can be configured to use automatic fitness evaluation). Artificial Painter is inspired by the artificial live survival game: an ANN with 4 inputs and 1 output is placed on a grid world in different cells, where it senses the angle and distance to two points. These 4 values are used as inputs to the ANN. The genotype of each individual is composed by the ANN synaptic weights, output function specification, coordinates and color mapping, as each output is assigned a different color. The population is composed by 16 individuals that produce 16 output pictures. These pictures are then evaluated by a user (fig. 9) and the best ones are selected for mutation and reproduction giving rise to the next generation [31].

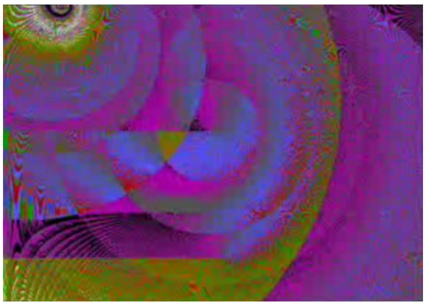


**Fig. 9.** Example of a picture created by The Artificial Painter (www.youtube.com)

### *4.3.3. Therapy: Hearing Aid Tuning*

Hearing aids have a lot of parameters to adjust in order to achieve the maximum quality for each user. This is due to the fact that the quality of hearing is a personal and subjective experience: "no one can perceive what others year" [6].

The traditional approach involves measuring hearing parameters by means of audiograms and then adjusting the apparatus parameters. In practice, this procedure does not guarantee a good hearing quality as the tests can not cover all the complexity involved in the hearing process, besides taking a lot of time.

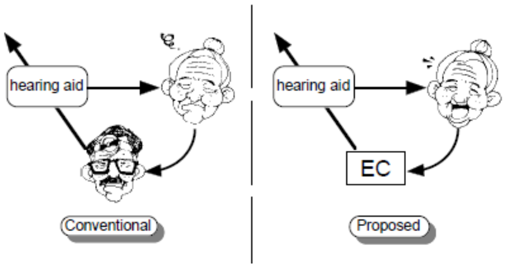



**Fig. 10.** IEC application in therapy - hearing aid fitting [6]

With IEC there is no need for previous examinations and the tuning process is guided by the user (fig. 10). Besides that the hearing aid can be tuned in different environments such as pure speech, speech with background noise or music.

## 5. Conclusions

The IEC paradigm is based on computational models that comprise a direct and active human intervention. In these techniques the adequacy values, expressed by fitness values of EC algorithms, are estimated by a human being. The general scheme of an IEC algorithm is very simple: the user interacts with the IEC system trough the interface evaluating the outputs evolved by the EC application, responsible for applying the crossover and mutation mechanisms in order to produce the next generation based on the user past individual selections. Therefore, the IEC is a technique that allows collecting the user's preferences that include its intuition, emotions and other psychological aspects.

The main problem in IEC is user's fatigue, as the paradigm places humans interacting with tireless computers. Various approaches - including automatic and human combined evaluation mechanisms - have been used to overcome this problem but, as long as machines will not feel emotions or have not aesthetical sense, it seems there is still a long way to go.

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