# Towards Agent Device Ontology as Genotype

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**Abstract:** In a future of pervasive and contextually aware computing, the knowledge and understanding of mobile device attributes and capabilities will be a key enabler. Software engineers and developers will benefit from the understanding of possible device configurations which represent optimal market solutions. This paper discusses the first of a several phase investigation using the techniques of evolutionary computation to construct a multiobjective optimisation model and system. The overall goal is a system to provide insight into the potential device configurations that a software engineer might face in the future. Through the use of biological analogy, the problem suitability for co-evolutionary design and the foundation of a mobile device genome will be presented.

## 1 Problem Domain

The motivation for this work is the great difficulty found in engineering and deploying mobile context-aware applications in the current heterogeneous network. This paper outlines the first in a series of investigations around the application of evolutionary theory to the pervasive computing device environment. The model constructed provides genome representation, one of the critical structural elements of any adaptive plan.

Pervasive computing promises a future environment of networked sensors, computing devices, and information appliances. The ability to develop solutions for this plethora of devices will affect many throughout industry. For the software engineer developing new services, a future of continuously changing deployment platforms is not a welcome sight. To the product development professional, the concept of an expanding landscape of multi-device networks in the home and workplace will also represent a confusing array of potential customers, some who can be reached and others who cannot not. Worse yet, the implications for interoperability and integration are significant. If the future vision of pervasive computing is to be realized and managed, there needs to be the ability to understand and even potentially forecast what this device space looks like within a specific market segment. The problem then becomes understanding the multivariate landscape of devices and looking for sets of solutions in those landscapes which might be optimally positioned to serve the market.

As stated, the problem begins to look much like that found in biological evolutionary theory where there are many organisms competing for a scare resource and those which are optimally adapted for the landscape survive. As the landscape or environment changes those most capable of adapting do so and continue to evolve to represent the fit solution.

In Section 2, we will introduce at a very high level the concepts and constructs behind genetic algorithms. In Section 3 and 4, we will review the idea of representing devices as digital organisms with the FIPA device ontology as their genotype. We will discuss encoding of the genotype into a machine readable format in Section 5 and the planned next steps appear in Section 6.

## 2 Introduction to Genetic Algorithms

Genetic algorithms are mathematical models which utilize parameterised functions to search a space of potential solutions locating those solutions which are deemed fit relative to a goal or objective. Evolutionary computation is based on the principles of evolution found in nature, the solutions are not programmed but they emerge in much the same way as the fit species emerge in nature [1]. It is important to understand that these algorithms do more than simulate the aspects of evolution, they actually evolve the solution without a priori knowledge. The search space bounds need to be known but the solutions which can be initialised at the start of the epoch do not. Genetic algorithms inherit from their biological forerunner, various important concepts which help to underpin their operation. The most important are selection, recombination or crossover and mutation [2]. Selection is of course, the selection of fit solutions based on the objective, and recombination or crossover is the method to uniquely combine the attributes of one encoded solution with those from another. In a later section, we will return to the notion of encoding genotypes which is a central issue for the efficacy of the algorithms themselves.

The algorithm then operates to create generations of solutions in order to evaluate the fitness of each individual solution, $N$ relative to the entire population as to how it performs on the objective function. It is critical that the objective functions mathematically represent the solution desired, and a particularly important component of designing genetic algorithms (GA), and specifically designing what is called competent genetic algorithms, is the problem representation itself [3].

## 3 Mobile Device Evolution

Context awareness has been and continues to be an area of active research. As that research begins to be brought into a commercial setting, the mobile application developer is presented with a vast array of platforms, development environments as well as the unique reconfiguration support requirements of context awareness [4]. There are several standards emerging for dealing with understanding, specifying and implementing device contextual reconfiguration, these in themselves do not forecast the deployment landscape of the future for mobile software developer. If we understood the dynamics of change around the mobile device attributes and platforms, the features and functional building blocks that would evolve given a set of market parameters, then engineers would be better positioned to design models and build optimal software solutions for these potential device configurations.

This is the basic thesis for this work. Can we understand and potentially design for mobile devices as digital organisms? [5] As a first experiment, let us consider the nature of current mobile devices and determine if we can satisfy the four postulates of Darwin's Theory of Evolution. Given we can logically prove that mobile devices adhere to these four postulates, and we will then progress the work by creating the necessary models and experiments.

Taking the postulates from the famous "The Origin of Species" completed by Charles Darwin in 1859, we have firstly, that "individuals within the species are variable", commonly referred to as variation. The mobile device marketplace is composed of laptop computers, handheld computers, PDA's, and mobile phones primarily. Let us consider each of these its own "species". Ignoring for a moment the global market and just focusing on the UK marketplace, there are currently no less than fifty eight (58) different models of mobile phones on the market, competing for market share. It is clear that variation is present in mobile device species. The second postulate is "some of the variations are passed onto offspring", called inheritance. Staying within the mobile phone species, we find product families designed with similar features sets for several generations, creating a clear descendant set of properties. Product families are designed such that feature sets and attributes are selectively inherited where the market has deemed them successful. The third postulate, "In every generation, more offspring are produced than can survive", also known as abundance. Research into the number of discontinued mobile phones finds there are many which did not survive to the next generation either because of technology obsolescence or purely market demand as documented by insufficient market share [6]. However, while on the surface this appears to validate this postulate, there are several research questions regarding the definition of a generation in this context. The final of Darwin's postulates is "individuals with the most favourable variations will reproduce or reproduce the most" which is at the heart of the evolutionary theory. In the mobile device arena, although reproduction is not a direct analogy due to the non-biological nature of the population, the economic market provides the selection mechanism. Variations in feature sets which map onto customer demand fuel the statistical distribution of market share. This is the economic model of selection in the digital organism population. The four postulates can be seen to hold when applied to the mobile device market. This coupled with the technological problem of engineering optimal solutions for this market give sufficient grounds for the development of an evolutionary computation system with which we can model this environment.

## 4 GA Design Strategy for MDE

The design of competent evolutionary algorithms is guided by the real world nature of the problem however, and a useful approach to such complex problems is first to perform a design decomposition process [7]. In using such biologically inspired processes, you cannot underestimate the importance of a suitable model as the basis to derive not only the genomic representation but to guide the formulation of the multiple objective functions [8]. The model of this problem space is multi-level in nature. The high level provides the general summary of the objective spaces, the lower level will provide the specific details of the devices as specified by the optimised genome. This concept is similar to one used by Parmee, et al in his investigation of co-evolutionary design, however we are not, at this stage, envisioning the architecture for a series of agents or looking at the automated design of the components [9].

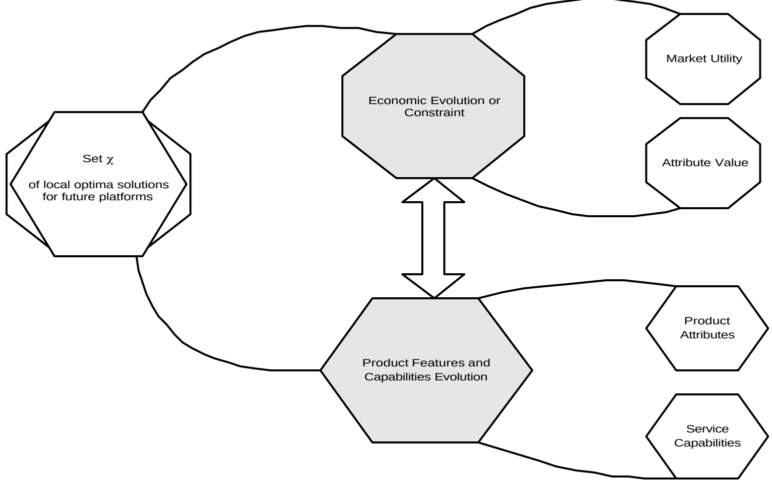


**Figure 1: Multi-level problem space**

The model we construct specifies a multi–tiered, multi-objective optimisation system as a first approximation to understanding the future of potential mobile device platforms. This system will not evolve to a single solution for a dominant mobile device design as multi-objective optimisation algorithms usually result in a set of optimal solutions or solutions which can no longer be optimised [10]. The result of the experiments with this software tool will be to provide an optimal set of device and service solutions given specific market constraints.

As a first measure to take a step towards this goal, the first in a series of multi-objective evolutionary algorithms must be designed. A standard process for such activity from[7] is as follows:

1. Design Decomposition – breaking down the component of the problem in the real world into suitable areas into which we can design
2. Model the problem space – in the areas of interest, model the problem or search space using the appropriate constraints, genome, parameters and objective functions
3. Integration of the approaches – integrating the models ad comparing the various significant controlling parameters both graphically and quantitatively, assisted by the appropriate visualization technique

Adopting this practice, the first step is to create a suitable model of the device evolution parameters and to form the foundation for selection and variation.

## 5 Mobile Device Genome Representation

A critical part of designing a competent evolutionary algorithm is representing the genome appropriately. The genome and its possible states should fully represent the possible solution but not with excess. For mobile device evolution though, we are in a position to experiment with previously derived representations which are developed for entirely different purposes. As we discussed above, much research work has gone into the development of semantically correct representations of devices and services [11]. We will leverage this work. One additional technique is required though, that is the building block hypothesis which specifies that short, highly fit solutions can combine to form even more highly fit solutions [12]. The details and benefits of the building block hypothesis for use in the exploration and exploitation of the search space are best found in [13].

The simplest available device ontology which will meet the experimental need is the Foundation for Intelligent Physical Agents (FIPA) device ontology which is used to specify the semantic description of devices on which intelligent agents will run [14]. Modelling of the device ontology using the Protégé 2000 knowledge-base development system results in a visual representation of the possible genome for the system. The building blocks can also be seen at the class level of the ontology itself.

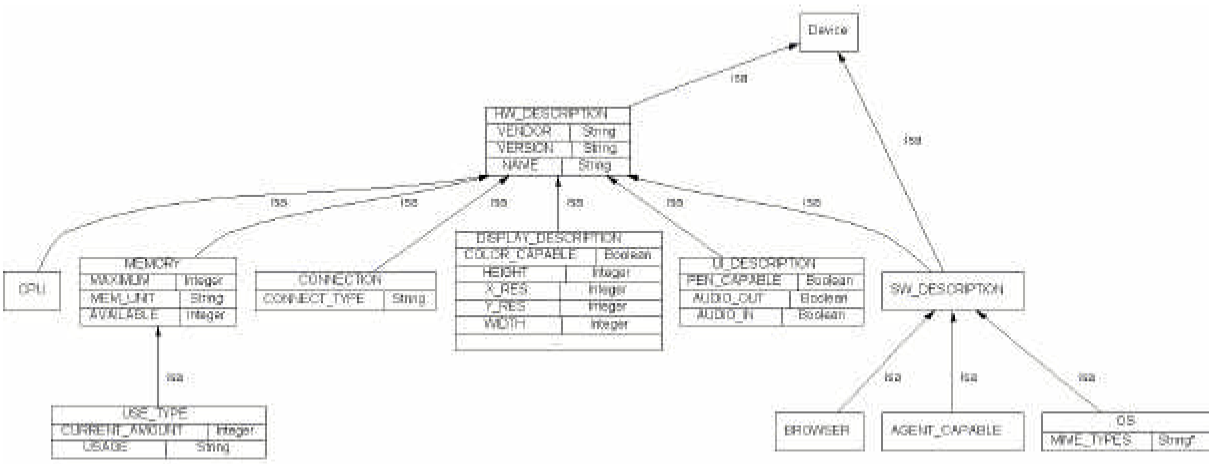


**Figure 2: FIPA device ontology**

We use the classes of memory, connection, hardware description, software description, and so on as our genetic building blocks. Each slot in the ontology then represents a specific gene in our chromosome. Descriptive instances in this first experiment have no significance and will be used as "introns" or non-coding components within the genome. The solution space is then defined by those solutions whose schema map back into this ontology [15]. The resulting expression of the genotype as defined by the genome is the physical device, this is analogous to the phenotype in biological systems.

One further step is necessary to represent these "attributes" to be used by the EA, the choice of encoding representation.

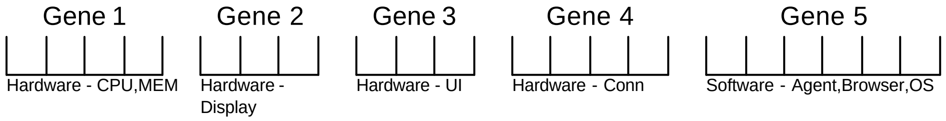


**Figure 3: Genome Representation – based on abstraction of FIPA ontology**

The representation in Figure 3 represents a "building block" style genome which will use binary encoding as a first phase. In subsequent phases, we will use real, integer and more natural representation, but binary with translation to meaningful values will allow early experimentation with the operating algorithm which can be tuned later.

Variation will be done as in [16] with crossover being limited to within the gene as this will maintain the feasibility of the design space. For example, crossover which spans the entire genome results in variations that are neither fit nor feasible.

## 6 Next Steps

The design methodology for evolutionary algorithms will be utilized with the next step to design the objective functions and any constraint functions such as penalties for unfeasibility. The design of the objective function is based on the work by Shapour Azarm at University of Maryland as well as works by Ofek and Srinivasan of Harvard and Stanford University respectively, guiding the formulation of a feature-based market share evaluation function. Using the knowledge-base as the input for a continuous, overlapping population "repository", the model which is built in Matlab will be then completed and testing will commence.

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