Assessing representation techniques of programs supported by *GreedEx*

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Abstract-In systems supporting learning of programming, it is common to use several techniques to represent algorithms, some of textual and graphical nature. This kind of representations is used by the *GreedEx* system, a system for interactive experimentation with greedy algorithms. The assessment made of this system thus far is based on the use of questionnaires and, therefore, on the subjective perception of the student with respect to the *usefulness* and/or *complexity* of the representations provided. This paper presents two empirical evaluations conducted with the aim of learning about both aspects (usefulness and complexity) of each of the representations supported by the *GreedEx* system. In this evaluation several information sources are combined: subjective perception questionnaires and the metrics provided by an *eye-tracking* device.

***Keywords*—Programming learning, empirical evaluation, *eye tracking*, motivation.**

I. INTRODUCTION

Programming learning tools often exploit the use of different representations of algorithms, since they facilitate their understanding by students. Within the LITE research group at the Universidad Rey Juan Carlos (URJC) in Spain, a tool to learn greedy algorithms, called *GreedEx* [1], has been developed. This tool supports several types of representations (of a graphical and textual nature).

In this paper, we describe two experimental experiments to assess the representation techniques supported by *GreedEx*. Particularly, we are interested in finding out what the *usefulness* and *complexity* of each representation is. These assessments have a broader objective than other previous analyses, mainly based on the use of questionnaires. The results obtained in these previous studies have a large subjective component and therefore, the conclusions drawn may be subject to bias. In this work, we intend to improve the previous assessments, incorporating more objective measures, provided by an *eye-tracking* device [2]. *Eye tracking* sessions allow us to draw conclusions about the behavior of visual exploration that users carry out when they are looking at a certain image or user interface. Since by using this technique we collect measures of a physiological nature, the obtained results can not be controlled by the users and are not as such subject to bias. This technique has been successfully applied to various fields, however, we would like to highlight its application in evaluating the usability of interactive systems, especially web-based systems [2] [3].

This paper is organized as follows: in the next section, the *GreedEx* tool and the representations that it includes are described; in section 3, we discuss the details of the two empirical studies and the results obtained; and finally, we present the conclusions drawn from this work and the main lines of future work.

II. THE GREEDEX SYSTEM

The *GreedEx*[1] (*GREEDy EXperimentation*) system [1] is an interactive assistant used to learn greedy algorithms. *GreedEx* supports an experimental method. A student selects one particular problem from a set of available problems and the system allows him or her to experiment and observe the results obtained when applying different selection functions. The student launches the application and carries out an iterative process: first he/she generates input data to a specific problem and, after that, executes the greedy algorithm using all (or most promising) selection functions.

The *GreedEx* user interface (Figure 1) consists of three main areas:

- *Theory panel*. It occupies the lower left area of the interface (Figure 1). This area includes two tabs, one to show the problem statement, and the other tab shows a generic greedy algorithm that solves it.
- *Visualization panel*. It occupies the upper area of the interface, and shows the graphical representation of the problem. In Figure 1 we can see, for the "knapsack

[1] http://www.lite.etsii.urjc.es/greedex/

problem”, the set of input data (top left) and the appearance of the knapsack (top right). As the student simulates program execution, the selected objects move to be included in the knapsack. In “knapsack problem”, we have *n* objects (input) and we have to select a set of them to be inserted into a knapsack (output). Each object has a weight and the knapsack has a maximum capacity. The objects are shown graphically (ordered by weight) and organized left-to-right by the selection function of algorithm (the more to the left being the first selected object and the more to right being the last). All objects are painted with the same color and, when one object is selected, it is painted with a different color, and it is introduced into the knapsack.

- *Table panel*. The lower right area contains four tabs that show different degrees of detail of the problem and the results obtained (in tabular format). Problem data are shown in the “Input data” tab. For example, in “knapsack problem”, this table shows the objects weights and the knapsack capacity. The “results” tab shows three columns: 1) the order in which the objects are selected, 2) the selected candidates and 3) value of the objective function (selected objects number). This description is shown for each selection function (selection strategy). In “summary” tab, value of the objective function is shown for each selection strategy. Finally, the “abridge” tab shows percentage of success of each selection strategy (i.e., percentage of optimal solutions found).

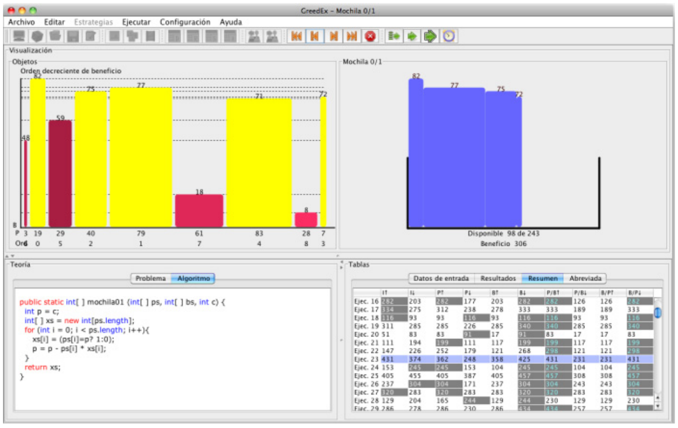

Figure 1. Appearance of the *GreedEx* graphical user interface for “*knapsack problem*”.

It is thought that *GreedEx* covers three levels of Bloom's taxonomy [4]; in particular, the levels of *analysis*, *comprehension* and *evaluation*. The tasks of analysis and compression of programs are complex from the cognitive point of view [5]. We believe that the use of several representations of algorithms, both graphical and textual, can be useful. Our goal, therefore, is to find out the extent to which the representations incorporated by *GreedEx* are useful and/or complex to students who are learning to program using this system. In the following section two assessments designed to test these aspects are discussed.

III. Assesment of Representations supported by GreedEx

In this section we describe two experiments performed to evaluate the techniques of algorithm representation supported by the *GreedEx* system. In both the purpose is to evaluate the *usefulness* and *complexity* of such representations. In this analysis two information sources are combined: one more indirect and subjective (collected through *questionnaires*), and another which is more objective (metric provided by an *eye tracker* device) [3].

A. *Experiment 1. Evaluating the static use of the GreedEx representation techniques.*

The first experiment involved a total of 13 students from a course called “*Design and Analysis of Algorithms*”, second-year students in the Software Engineering and Computer Science Degrees of the URJC, who agreed to participate voluntarily.

Before performing the experimental task, the students completed a ***pretest*** that allowed us to determine the *profile* of the participants. In the questionnaire, students had to rate their level of knowledge in programming, greedy scheduling algorithms as well as their experience in using the GreedEx tool and the representations that it incorporates on a *Likert* scale (1 to 5). The analysis of data collected through the *pretest* allowed us to verify that all participants were familiar with the basics of the greedy technique (M = 2.75 SD = 0.45), as well as with the experimental method supported by *GreedEx*. In turn, ten of the participants had used this environment (M = 2.83 SD = 0.72), so they could figure out the representations that this system supports.

Once the *pretest* was filled out, students went on to perform the ***experimental task***. This task was to determine the optimal selection function for the “*knapsack problem (version maximize the number of objects)*”. Students visualized the four possible selection strategies that *GreedEx* identifies for this problem on a screen and without a time limit. For each of the four solution options, the three representations provided by the tool are displayed: the graphical representation of the objects to select and the knapsack, the program code and execution trace in a tabular format. For each alternative to be chosen, an incomplete solution (three-quarters of its execution) is displayed. Therefore, in this initial assessment an evaluation in its static mode is hoped to be made, the three representations provided by the *GreedEx* system.

During this phase ***eye-tracking*** equipment was used. This device is able to track the user's gaze; that is, the order of visual exploration of the representations displayed on screen as well as the time spent looking at each of them, or the number of times consulted. During an *eye tracking* session a great amount of information and metrics is collected [3]. Most of these metrics are related to the number and duration of the so-called *fixations*, which are obtained by the stabilization of the eyes in an area of the image (the so-called *areas of interest* or AOI), for a certain period of time. From fixations, a graph (the called *scan path*) can be obtained (Figure 2), that indicates the order of visual exploration of the elements shown in the visualized image.

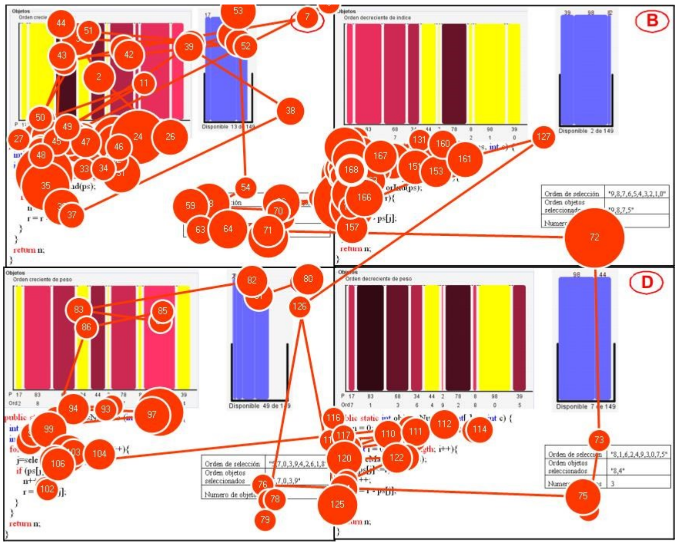

Figure 2. Example of *scan path* (graph created from *fixations*) generated by a student in experiment 1.

From fixations we can extract a large number of metrics that can be interpreted as measures of interest, cognitive load, emotional arousal, etc. For example, the *total number of fixations on an AOI* can indicate interest or *usefulness* of the information displayed on this area to solve a given task. This interest can also be inferred from the *total time spent to inspect* this AOI. Meanwhile, a higher *average duration of fixations on an AOI* indicates greater difficulty to understand and extract information from that area. All these metrics are, therefore, direct measures of *visual effort* that is required to understand the information shown, and indirect measures of *cognitive processing* associated with such effort.

As discussed above, the objective of this experiment was to evaluate the interest (*usefulness*) of each of the representations provided by *GreedEx*, as well as the *complexity*, or cognitive effort associated to analyze and understand each. To accomplish this, it was necessary to define the various AOIs for which we wanted to calculate the above-mentioned metrics. We defined an AOI for each alternative solution to be selected (and thus inspected) by the students (A, B, C and D), and in addition, for each of these areas, three additional AOIs that delimitated each of the provided representations (*AOI-Graphic*, *AOI-Code* and *AOI-Table*) for each alternative option of solution. We, therefore, defined a total of 16 AOIs.

Once the tasks to solve were completed by students, they went on to complete a ***posttest***, in which they rated the *usefulness* and *complexity* of each of the three representations on a *Likert* scale of 5 points (with 1 being the lowest score and 5 the highest). With this questionnaire we intended to ascertain the *subjective perception* of the participants regarding these issues, to subsequently, contrast this opinion with the data supplied by the *eye tracker*.

Another aspect we are interested in is the students' ***motivation***, since the type of motivation or the interest shown during activity can determine their behavior and affect the results. There are several theoretical frameworks about motivation. The *self-determination theory* is a well-established framework to study this issue. Self-determination [6] states that there are three levels of motivation:

- *Intrinsic motivation*. It refers to doing something because it is inherently interesting or enjoyable. When intrinsically motivated, a person is moved to act for the fun or challenge entailed rather than because of external prods, pressures, or rewards.
- *Extrinsic motivation*. This type of motivation occurs when the person performs a task, not for its own interest, but for the incentives or benefits to be gained from its realization. This level of motivation is split, in turn, into two types: *external regulation* and *identified regulation*. When there is external regulation, the subject performs the task only for the reward or punishment that can be derived from it. Identified regulation occurs when the subject finds himself or herself obliged to perform the task or behavior, either because he or she believes that others consider it important or because he or she believes it to be beneficial.
- *Amotivation*. The least self-determined dimension, implies non-regulation and occurs when individuals do not perceive the contingencies between the behavior and its consequences, and behavior lacks intrinsic or extrinsic motivators.

These levels of motivation are valued by individuals with positive effects (intrinsic motivation and identified regulation) and negative (external regulation and amotivation). There are several instruments to measure motivation. In this work we use the *Situational Motivation Scale* (SIMS), and in particular its translation and adaptation to Spanish [6], which has been successfully used in educational environments. This scale includes 14 items, which measure the intrinsic motivation, identified, external regulation and amotivation. Each item consists of a *Likert* scale, ranging from 1 ("does not correspond at all") to 7 ("corresponds exactly"). The high valuations on some items are considered a negative element. For example, a high valuation on item 3 ("Because I am supposed to do it") indicates negative motivation in general. The values of these negative items have been inverted in the statistical analysis.

B. *Experiment 1. Results and discussion.*

In this section we discuss the results obtained in this first experiment.

Regarding the ***usefulness*** of different representations and taking into account its assessment on the *posttest*, students considered the tabular representation as the most useful (M = 4.08), followed by the graphical representation (M = 3.75), being the source code which obtained the lowest score (M = 3.25). The two metrics provided by the *eye tracker* device to measure user interest in a certain area of the image (AOI) are the *number of fixations* (#Fij) and the *inspection time* (TInsp) of the AOI. Since, in analysis activity that solved the students there was no time limit, it is more appropriate to consider, instead of absolute times, relative times, i.e. the *percentage of inspection time* (%Insp) spent by each subject to inspect each of the representations with respect to the total time devoted to analyzing the entire image. In Table I we see the values obtained for all these measures. We can see that there is no consistency between the subjective perception of students regarding the usefulness of different representations and information provided by the eye-tracking device. While students considered the table to be most useful ($M = 4.08$) and the code least useful ($M = 3.25$), their visual behavior revealed that the source code and graphical representation were the most consulted items to perform the activity (greater number of fixations and longer inspection time), being the source code to which more time was dedicated (%Insp = 38.25).

TABLE I
SUBJECTIVE PERCEPTION AND MEASURES PROVIDED BY THE EYE TRACKER FOR ASSESSING USEFULNESS OF THE THREE TYPES OF REPRESENTATIONS*

AOI	Perceived Usefulness*	#Fij*	TInsp*	%Insp*
Graphic	3.75 (1.14)	**85.67 (50.01)**	31.89 (18.19)	32.08 (11.46)
Code	3.25 (1.29)	66.17 (33,70)	**40.60 (26.43)**	**38.25 (16.11)**
Table	**4.08 (1.08)**	56.08 (20.03)	27.73 (12.96)	29.67 (14.52)

* The mean scores and the standard deviations are shown (in parentheses).

TABLE II
SUBJECTIVE PERCEPTION AND MEASURES PROVIDED BY THE EYE TRACKER FOR ASSESSING COMPLEXITY OF THE THREE TYPES OF REPRESENTATIONS*

AOI	Perceived Complexity*	Average Fixation Duration*
Graphic	2.33 (1.15)	0.34 (0.05)
Code	**2.83 (1.03)**	**0.56 (0.23)**
Table	1.75 (1.06)	0.49 (0.17)

* The mean scores and the standard deviations are shown (in parentheses).

Regarding the ***complexity*** of each of the representations shown, and as seen in Table II, the participants believed that the most difficult to understand representation was the program code ($M = 2.83$), followed by the graphic representation ($M = 2.33$). The tabular representation wasconsidered the easiest to interpret ($M = 1.75$). As we have done before, these results were contrasted with those provided by the *eye tracker*. The metric for measuring cognitive processing is the *average fixation duration,* so that a higher value of this measure indicates higher cognitive effort and therefore greater complexity. In this sense, there is consistency between the subjective perception of the students and the value of this metric, so that the element which is most difficult to understand is the source code. However, while the element considered by students as the least complex is the table, the eye-tracking device indicates that the graph is the one that implies the least cognitive load.

In relation to the students' ***motivation*** during the task, it was generally medium-high ($M = 4.73$). The value of the lowest motivation was 3.14 and the highest was 6 (on a scale of 1 to 7). Figure 3 shows the relationship of student ratings in each of the four motivation dimensions. Most of students considered the task as important and beneficial for them (identified regulation dimension, $M = 4.73$). Many of them even wanted to participate just because they enjoy doing the activity (intrinsic motivation, $M = 4.32$). To a lesser degree they perceived it as an activity that had to be performed only because of their consequences (external regulation, $M = 4.26$) and less still they felt that they had no interest or consequence in the study of greedy algorithms (amotivation, $M = 1.48$).

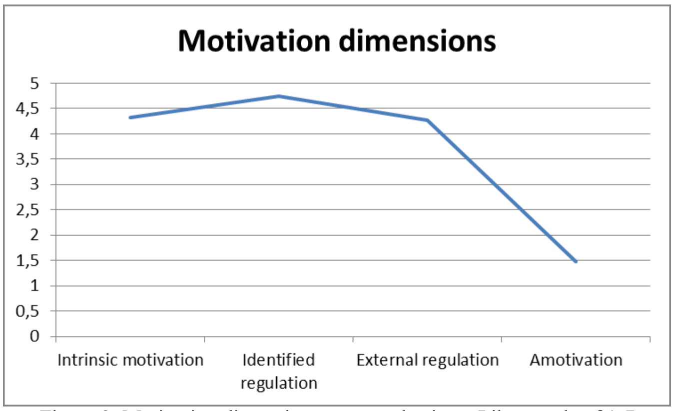

Figure 3. Motivation dimensions measured using a Likert scale of 1-7.

Following an ***analysis of correlations*** of all the dimensions considered in this study (subjective perception of the usefulness and complexity of the representations, the measure of student motivation and metrics provided by the *eye tracker*) was performed. Table III shows some of the detected correlations.

TABLE III
SOME SIGNIFICANT CORRELATIONS

#	Aspect 1	Aspect 2	Correlation coefficient (*r*)
C1	Code Usefulness	#Fij. Code	0.81**
C2	Code Usefulness	TInsp. Code	0.80**
C3	Code Usefulness	%Insp. Code	0.72**
C4	Intrinsic Motivation	Code Usefulness	-0.62*
C5	Intrinsic Motivation	%Insp. Code	-0.69*
C6	External Regulation	Code Complexity	0.70*
C7	Age	#Fij. Table	0.78**
C8	Age	TInsp. Table	0.72**
C9	*GreedEx* Experience	Graph Usefulness	0.61*
C10	*GreedEx* Experience	Graph Complexity	-0.69*
C11	*GreedEx* Experience	Average fixat.durat.Table	-0.84***

* $p < 0.05$ (Minimum significant correlation coefficient r for sample size $n = 12$ es 0,58).
** $p < 0.01$ (Minimum significant correlation coefficient r for sample size $n = 12$ es 0,71).
*** $p < 0.001$ (Minimum significant correlation coefficient r for sample size $n = 12$ es 0,82).

First, whether there were correlations between subjective perception measures of *usefulness* and *complexity* and the *eye tracker* metrics were examined. We only found a clear relationship between the perceived usefulness of the code and the three metrics to objectively measure this characteristic: number of fixations on the source code ($r = 0.81$ $p = 0.05$), time spent inspecting this representation ($r = 0.80$ $p = 0.05$) and the percentage of inspection time compared with the time spent on inspecting the other representations ($r = 0.72$ $p = 0.05$).

Regarding *motivation*, a negative correlation between intrinsic motivation and the source code usefulness ($r = -0.62$ $p = 0.05$), and the percentage of time devoted to visually inspect it ($r = -0.69$ $p = 0.05$) have been detected. Meanwhile, the perceived complexity with respect to this element correlates positively with the external regulation (r = 0.70 p = 0.05). We believe that this latter correlation may be due to the fact that students often use the source code in knowledge evaluation activities (such as exams), which normally are perceived as compulsory activities, by which there is little to no pleasure derived, and the students perform for the positive or negative consequences that it has.

Another relationship that has caught our attention is that which occurs between age and the number of fixations (r = 0.78 p = 0.01) and inspection time (r = -0.72 p = 0.01) on tabular representation. It seems that the older students spend more time inspecting this element over the others.

Experience in the use of the *GreedEx* tool also correlates with the consideration of the graph (r = 0.61 p = 0.05) as more useful and with consideration that this representation is less complex (r = -0.69 p = 0 05). We see, therefore, that the experience of using the system influences the subjective perception that students have with respect to this representation.

C. Experiment 1. Evaluating the dynamic use of the GreedEx representation techniques.

The first experience performed allowed us to obtain a preliminary evaluation of the visualization techniques of *GreedEx*. However, the task to be solved by the students differs of the task that the participants can perform using this system. The full potential of this application, and the representations that it incorporates, lies in the ability for simulating the algorithms. Therefore, in this second experiment, we made the evaluation of the representations after solving a task using the *GreedEx* tool. In this second experiment a total of 6 students from the URJC were involved.

As was done in the previous experience, before beginning the activity, students completed the same ***pretest*** made for experiment 1. The *profile* of the participants was similar to that of the students who participated in the previous assessment, although in this case their knowledge in using *GreedEx* were somewhat higher (M = 3.50 SD = 0.55).

The problem statement of the ***experimental task*** that students had to perform was the following: *"There are n objects, each of them with a weight ps [i], 0≤i≤n-1, and two knapsacks with capacities c1 and c2. The objective is to maximize the number of objects that are introduced in both knapsacks without exceeding their capacities. They are asked to find the optimal selection functions for this problem, among those proposed by GreedEx".*

After finishing the exercise, students completed the same ***posttest*** used in experiment 1, which allowed use to ascertain the subjective perception of the participants regarding the *usefulness* and *complexity* of the three representations supported by *GreedEx*.

D. Experiment 2. Results and discussion.

In this subsection we discuss the results of the second experiment.

Regarding the ***usefulness*** of the different representations (Table IV), students considered, as happened in experience 1, that the tabular representation turned out to be the most useful for solving the task (M = 5.00), followed by the graphic representation (M = 3.50), while the source code obtained the lowest rating (M = 2.33). In contrast to the previous study, in this case, the metrics calculated by the *eye tracker* to measure user interest in each AOI (#Fij, Insp and %TInsp) were consistent with the subjective opinion of students. All three measures indicate that the element to which participants paid more attention (and, therefore, they found more useful to solve the task) was the tabular representation, followed by the graph, while the source code was considered as less useful for solving the problem proposed.

TABLE IV
SUBJECTIVE PERCEPTION AND MEASURES PROVIDED BY THE EYE TRACKER FOR ASSESSING USEFULNESS OF THE THREE TYPES OF REPRESENTATIONS*

AOI	Perceived Usefulness*	#Fij*	TInsp*	%Insp*
Graphic	3.50 (1.05)	479.00 (333.39)	108.96 (73.21)	40.17 (16.10)
Code	2.33 (1.51)	69.83 (66.72)	15.27 (18.92)	6.28 (7.65)
Table	**5.00 (0.00)**	**570.17 (292.31)**	**157.91 (101.38)**	**53.55 (17.54)**

* The mean scores and the standard deviations are shown (in parentheses).

TABLE V
SUBJECTIVE PERCEPTION AND MEASURES PROVIDED BY THE EYE TRACKER FOR ASSESSING COMPLEXITY OF THE THREE TYPES OF REPRESENTATIONS*

AOI	Perceived Complexity*	Average Fixation Duration*
Graphic	3.33 (1.03)	0.24 (0.06)
Code	3.17 (1.33)	0.21 (0.07)
Table	**3.67 (2.07)**	**0.26 (0.09)**

* The mean scores and the standard deviations are shown (in parentheses).

Regarding the ***complexity*** of each of the representations displayed (Table V), the students in this case believed that the tabular information was the most difficult to interpret (M = 3.67), followed by the graphic representation (M = 3.33), while the source code was the least complex (M = 3.17). As occurred with the *usefulness*, again, in this case, the metrics calculated by the *eye tracker* are consistent with the assessment made by the participants. The element that imposed greater cognitive load (as measured by the average fixation duration) was the tabular representation (M = 0.26), followed by the graphic representation (M = 0.24), being the source code which required the least visual effort (M = 0.21).

In Figure 4 the subjective evaluation made by the participants in each of the two experiments conducted can be seen and compared graphically.

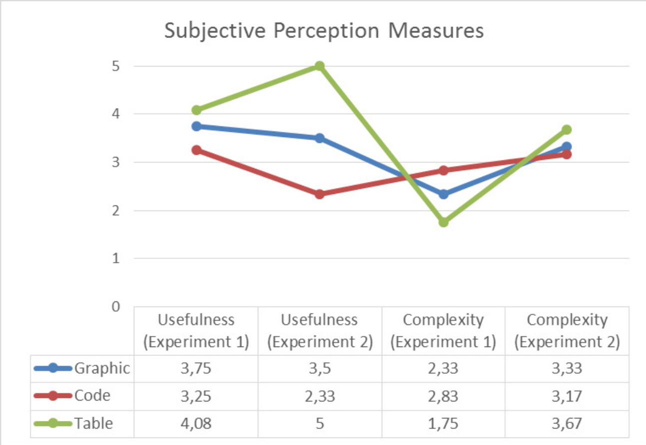

Figure 4. Comparison of subjective assessments of usefulness and complexity of each of the representations in the two experiments.

IV. CONCLUSIONS AND FUTURE WORKS

The use of multiple representations of programs is common in *software* systems for teaching Algoritmia, especially in those that support execution and simulation of programs, such as the *GreedEx* system. With the aim of improving the learning experience of students with this system, we have carried out two experiments in order to assess the representations that this system supports. In these experiments, the information collected by means of subjective perception and motivation questionnaires was combined with the information that an *eye-tracker* device provided us.

In the first assessment, the three representations supported in *GreedEx* were shown in a static way. In this case, students felt that the most useful representation was the tabular one. However, the *eye-tracking* device indicated that the source code was the most consulted representation. In terms of complexity, the participants indicated that source code was the most complex element and, in this case, this was consistent with the information supplied by the *eye-tracking* device.

However, the static use of such representations could not be considered conclusive, since the real potential of *GreedEx* lies in its ability of simulation and stepwise execution. Therefore, a second experiment to solve an activity using *GreedEx* was performed. In this experiment, the participants had to use the simulation features of the tool and then they valued its representations. In this second experiment, the results were consistent between the valuation that the students gave (subjective measures of usefulness and complexity) and the measures obtained by means of the *eye-tracking* device (objective measures). In this case, the students considered that the most useful element was, again, the tabular representation, while the source code was the least valued representation. Regarding complexity, the students indicated the table as the most complex element and the source code as the least.

Therefore, it was found that the source code was the most used representation by students when a snapshot of the program execution (the static version) was shown. However, in the context of a dynamic simulation of the program, the students preferred to observe the evolution of the tabular and graphical representations, although they believed that the information provided may be more complex to analyze and to understand. In future research, we plan to address the analysis of the use of each type of representation throughout the time taken by students to solve the exercise. That is, to assess whether the students consult some representation more than another one as they advance in the simulation and execution of the algorithm and in the process of solving the problem.

Another line of future work is the detailed analysis of the generated *scan paths* and their possible relationship with the learning styles of the students [7]. The objective of this study will be the identification of different *programs analysis patterns,* which can depend on each learning style. It is necessary to note that in the first of the experiments that we have carried out, we also collected information about the learning styles of the students. However, we could not find out significant relationships between learning styles and preferences or opinions regarding the usefulness and complexity of the different representation techniques. Perhaps, the small size of the sample could have influenced these results. Therefore, we also plan to increase the size of it in our next experiments.

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