Analysis of Relationships among Diverse Types of Software Attributes for Assessing Quality Factors of Gaming Software

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Summary
The goal of this paper is to present a novel approach for assessment of the quality of Gaming software in terms of factors formulated by correlating its diversified attributes. All possible descriptive properties of customers, users and software products of the class Games were gathered under the three categories of 'customer attributes', 'user attributes' and 'engineering attributes'. The attributes were then put into category to category correlation and reduced. Some feed backs from the environment of functioning of the system were also considered to verify the reduction procedure and use the attributes for the purpose.
Key words:
Software attributes, customer relationship management, gaming software, quality factors, quality assessment.

1. Introduction

Quality Function Deployment (QFD) [1-2] or House of Quality (HQ) method has been proven to be a very useful tool for total quality management. The very idea underlying the method seems very interesting for the scope it provides. A product or service, when represented in a space defined by diverse types of attributes is provided with numerous avenues for getting assessed.
Quality assessment itself is a difficult issue. And the problem with measurement of the features of a software product turns the problem of determining quality factors of it even harder. So, for quality factor assessment of gaming software we searched for effective methods and models that are in practice for marketing and management of other products. We thus came up with the idea of using QFD method. We assumed that a simple adaptation of the method to our problem may be very fruitful. In place of Engineering and Customer attribute correlation and perceptual modeling we propose an extension for more explicit processing. Besides, engineering and customer attributes we have proposed user attributes as well to capture in a more quantified way the factors down to the users of the product. And we have suggested to use numerical assessment values for correlating diverse types of attributes.
Research activities of the computer community around Customer Relationship Management (CRM) were very inspiring for our efforts. A 'Call for Papers' for a special issue of IEEE Transaction on Knowledge and Data Engineering on 'Customer Relationship Management' that was planned to be published early 2007 is to be mentioned in this regard. Topics of interest of the issue and the computational challenges it highlighted were just attractive for explorative research. A number of research works on CRM is available, [3-5]. Study of the works opens some facts. Most important of those is that it is vital to take into consideration customer opinion in finding the quality factors measured in terms of product descriptors.
Use of different attributes of products for quality assessment has its reference in different research works like [6-7]. We have explored the idea and proposed a procedure to quantify various attributes pragmatically. We finally come to the point at which we are able to describe the quality of gaming software in terms of its engineering attributes and recommend individual products to specific groups of gamers. And this idea has also its predecessor in [8].

2. Gaming Software in Attribute Space

In reference with the QFD method[1-2] we propose, with some enhancement, a methodology that involves three types of attributes to describe a product, namely, Engineering Attributes (EA), Customer Attributes (CA) and User Attributes (UA). Engineering Attributes are the attributes which show the characteristics of what is used. That is, for instance, we can define a product in terms of EA, measurable features popular to the designers and manufacturers of the product. Customer Attributes reflect

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the customers' point of view about a product, i.e., what the customers say about the product. User Attributes contribute to our investigation by describing the characteristics of those who use the product. Quantification of the attributes with values chosen from various fuzzy and discrete quantifiers has been used to assess the relationships among the attributes. The attribute space of the Gaming software may include attribute similar to the following..

a. <u>Customer Attribute</u>
Attribute: sound effect
Possible values: excellent, good, not so good, bad, very bad
Attribute: complexity
Value: simple, easy, difficult, complicated
b. <u>User Attribute</u>
Attribute: age
Possible value: newborn, infant, child, youth, mid aged, aged
Description: Fuzzy, {(newborn, <2), (infant, 2-5), (child, 6-10), (youth, 11-22), (mid aged, 23-45), (aged, >45)},
Sample data: {x | x is areal number and x $\in$ [0, 120], x is measured in years}.
Attribute: gender
Possible value: Male, Female
Description: Discrete (Binary), {(Male, 1), (Female, 0)}
c. <u>Engineering Attribute</u>
Attribute: sound
Possible value: {funny, joyous, action, horror, special event}
Attribute: type of game
Domain: - (strategy, action, race, arcade, puzzle, text, adventure)

Finally we get three different sets of attributes to describe Gaming software from different perspective.

3. Correlating Diverse Types of Attributes

As our assumption stands, quality of Gaming software can be assessed in terms of EA taken in correlation with CA and UA. Keeping it in mind ,we propose in line with the idea presented in [9], four different matrices to put EA, CA and UA in correlation with each other, in particular EA x CA, CA x EA, CA x UA and UA x CA. By EA x CA we mean that engineering attributes are put in correlation with customer attributes, that is, EA arranged in rows and CA in columns. In fact we ultimately arrive at EA x UA using CA as associating elements between EA and UA. It is also to be marked that we distinguish between EA x CA and CA x EA. It means that shift in values of an EA due to the shift in values of a CA is not bound to be equal to the shift in values of a CA due to the shift in values of an EA. It is simply because EA and CA are quantified from diverse perspectives.
The value in a cell of a matrix is set based on expert opinion. In the EA x CA such a value will mean expert's ranking in a scale the change of quantified value of the specific EA with the change of quantified value of the corresponding CA. To assess the correlation in this way by a domain expert, we think, is possible and justified. Sample entries in the EA x CA may look like the ones shown in Table 1, where the domain of (ΔEA) / (ΔCA) is {0, 1, 2, 3, 4, 5}.

TABLE 1: SAMPLE ENTRIES IN EA X CA MATRIX

	ca1	ca2	ca3	ca4
ea1	0	1	3	1
ea2	1	1	0	0
ea3	0	0	1	1
ea4	0	2	1	4

4. Reduction of Engineering Attributes and User Attributes

The idea behind reduction of attributes is that if an attribute of one type is not related substantially to any of the other type that is put on correlation in a matrix described above is to be discarded. Consider a X x Y matrix that stands for EA x CA. Assume that engineering attributes are placed in rows and customer attributes are placed in columns. Similarly the Y x X matrix stands for CA x EA. Now, If M_{ji} represents a value in the matrix in the j^{th} row and i^{th} column. Then, the significance of the j^{th} row in either X x Y or Y x X can be calculated as follows.

$$\sigma = \sum_{i=1}^{m} M_{ji}$$; m represents the number of columns in each row

In the case of reducing attributes of X with respect to Y, If this calculated significance is less than a defined threshold α, while no entry in that j^{th} row is above average, then it may be considered irrelevant with respect to all given attributes of Y, and is discarded. Then we re-construct the Y x X matrix using the reduced number of attributes of X and perform the same procedure on Y x X matrix and try to reduce an attribute of Y. The process of reducing attributes are carried out until no more attribute in X x Y or Y x X matrix can be discarded. The major steps of the algorithm are presented below:

Algorithm: *Reducing the attributes of X and Y using the matrices X x Y and Y x X*
Begin

Step 1: Mark an irrelevant attribute of X using X xY;
Step 2: Eliminate the irrelevant attributes of X and re-construct X x Y and Y x X matrices using the reduced number of attributes of X.
Step 3: Mark the irrelevant attributes of Y using Y x X;
Step 4: Eliminate the irrelevant attributes of Y and re-construct Y x X and X x Y matrices using the reduced number of attributes of Y.
Step 5: Continue steps 1 to 4 until no irrelevant attributes in either X x Y or Y x X can be marked.
End

This process applied to EA x CA and CA x EA reduces EA in connection with CA, that is, we get reduced EA x CA. The same process applied to CA x UA and UA x CA will return reduced CA in connection with UA, that is, reduced CA x UA. Bringing together the reduced EA x CA and CA x UA by taking the common CA returns us the finally reduced sets of engineering attributes and user attributes (significant attributes) which are meant for further use in the methodology, in particular, in logical division of users and preparation of questionnaire. The flow diagram of the attribute reduction *algorithm* is shown in Fig.1

5. Logical Division of Users

The logical division, based on reduced user attributes (significant attributes), for example, age, education, etc., will classify the set of users. Different age groups will form, for instance, different classes. Combination of attribute values may be proposed to have finer classes. This helps us to target the appropriate users against whom the surveying to be done.
After the reduction process, the significance (σ) of an UA is determined by taking the sum of the entries in the corresponding column of the reduced CA x UA matrix. This significance is combined with the weights (given by experts based on the population, for example, age (infant: 0.01, child: 0.2, youth: 0.7), Gender (Male: 0.55, Female: 0.45)) of the sub divisions of the UA. As a consequence we arrive at a point where the importance of each division within a UA is evaluated.

6. Preparation of Questionnaire

The significant engineering attributes are taken into consideration, which contribute in the formulation of questions that are asked to the logically divided users. Much emphasis is given to the questions with highly rated (correlated) engineering attributes. Questions prepared in such a way are found to be an easy tool and very much to the point for the non technical people who are expected to respond.
Having the groups of users identified by logical division, we formulate a number of questions that reflect the importance of the EA. For doing so, the significance (σ) of individual EA is calculated as the sum of the entries in the corresponding row in the EA x CA matrix.

7. Quality Factors of Gaming Software in terms of Significant Attributes

The significant EA and UA turn to be the determining quality factors. The identification of the logical division of users based on UA and the types of questions to be asked based on EA finally leads us to the concluding step of our investigation. The questionnaire is finally distributed to the target groups of users and, responses are collected. A market survey is also performed in parallel to mark the most popular Gaming software. The characteristics of the software defined by their attributes are then observed and the significant EA are marked. The dominant attributes found in practice are then compared with our experimental significant EA and the proximity between them is measured. The closer the values are the more our EA contribute in the quality issue.

8. Experimental Verification

Here we present the outcome of our experimentation in the various numerical and graphical forms. Most of the primary data describing engineering, customer and user aspects of gaming software are collected from open sources. Working with the students of our university in this regard was very productive. We had a number of gaming competitions amongst our students. We also went to the children that use to game in the play centers of our neighborhoods. And our personal acquaintance with gamers helped us to add another group of people, the adults. The student group was the most populous with an approximate strength of about 300 young gamers. Next was the group of children of age below 11 years with the strength of about 100. The smallest group was of the adults comprising of 25 gamers of age over 25 years.
The data collected from different open sources for the three different sets of attributes were as follows:
Engineering Attributes: around 50, Customer Attributes: around 20 and User Attributes: around 80. The data collected in the form of attributes were put in different matrices, the correlation of attributes were determined and then the reduction process was carried out using the proposed algorithm.

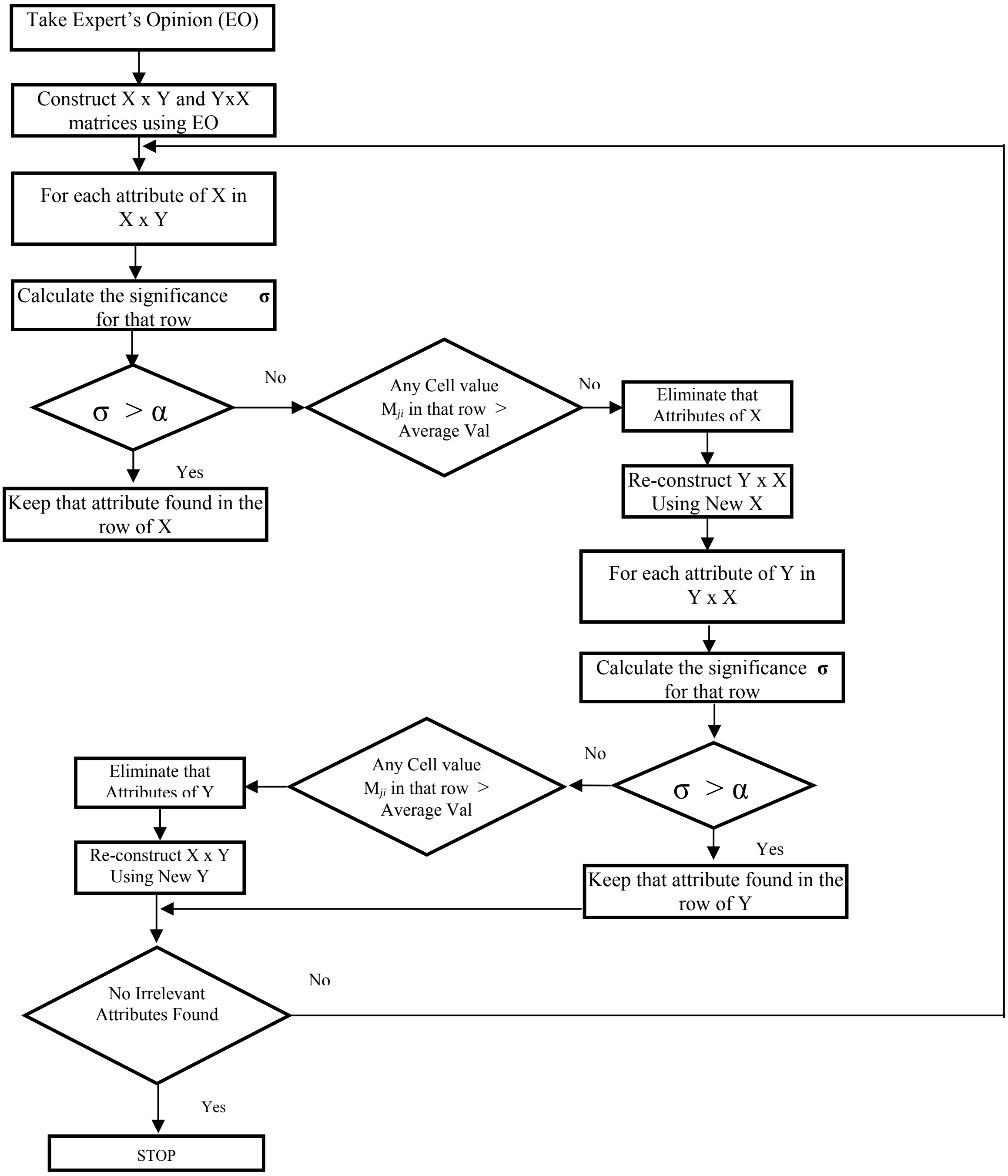

Fig. 1: The Flow diagram of the Attribute Reduction algorithm

In the reduced EA x CA matrix we had 20 EA and 8 CA, while in the reduced CA x UA matrix we had 6 CA and 30 UA. From the reduced matrices we ultimately marked 8 significant EA which were used to prepare the questionnaire.
We also marked 7 target groups of users involving significant UA from the reduced set. The responses of around 150 gamers of different target groups were collected. The analysis of the responses has been shown in the graphs below.

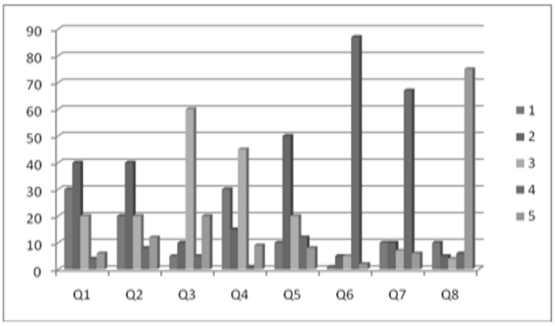

Fig. 2: Responses of the Student group

Fig. 2 depicts the responses of the student group on individual questions in a scale of 1 to 5, where for Q6 majority of students have rated it the highest scale of 5.
In Fig. 3 we see the responses of the children group on individual questions in a scale of 1 to 5, where for Q2 and Q4 almost 30% i.e. majority of the children have rated it the lowest scale of 1.

In Fig. 4 we see the responses of the Adult group on individual questions in a scale of 1 to 5, where for Q6 almost 85% i.e. majority of the adults have rated it a scale of 4.

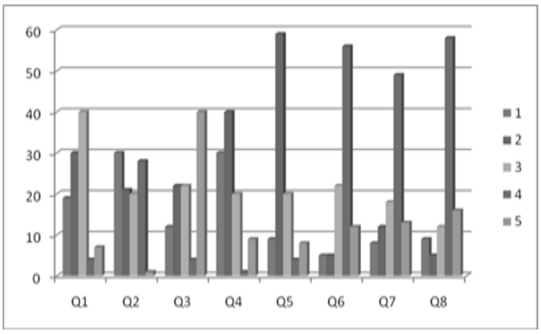

Fig. 3: Responses of the Children group

The graph (Fig. 5) reveals the total response of the students, children and adults on individual questions, where Q6-Q8 has been rated the highest by all the population of the three categories and the Q1 and Q2 the lowest. From Fig. 6, we can extract the individual questions' response of each target groups of students, children and adults. This explains the importance of EA on individual target group.

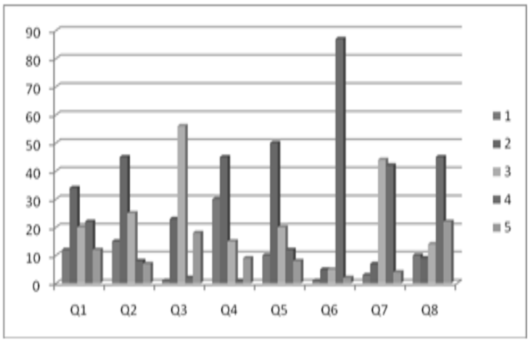

Fig. 4: Responses of the Adult group

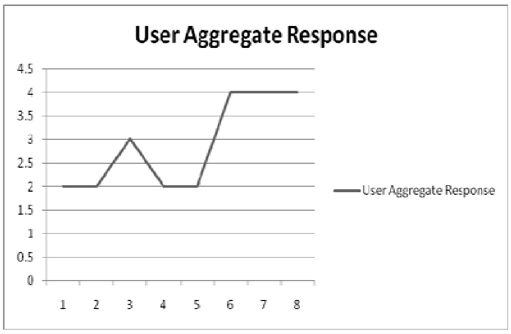

Fig. 5: Aggregate Responses of the User group

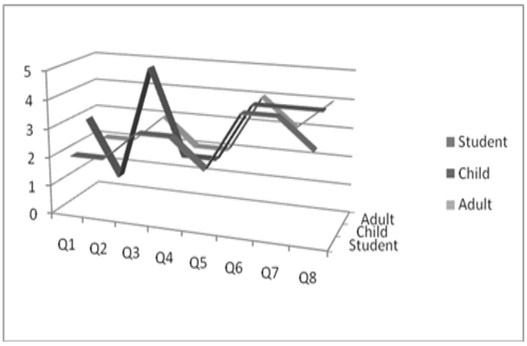

Fig 6: Categorized Population Responses

Analyzing the behavior of the gamers of different categories we choose, we concentrated on 10 most popular games like NFS Most Wanted, Age of Empires, etc. Differences between experimentally derived significant EAs and EAs of the most popular games have been plotted in the graph. (Fig. 7).
Some attributes showed no difference at all while others showed small differences. This justifies the usability of the proposed methodology to our satisfaction.

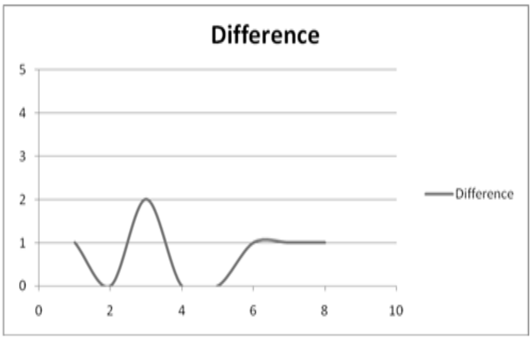

Fig.7: Difference between Exp EA and market EA

The differences thus obtained helped us to assess the role of the engineering attributes sensibly, and we arrived at very simple quality assessment criteria, determined by the significant engineering attributes.

9. Conclusion

Practical nature of the outcome of our investigation is to be marked first. The models and the methodology proposed here for discovering facts in a world which is very poorly quantified come out to be quite realistic. Quality factors described in terms of measurable engineering attributes rated by the users of the product, we, think are supposed to be 'close to the earth'. So, we would like to highlight this side of our work most.

A lot has to be added to the approach we present here. It is a report of an ongoing research and we hope to apply the proposed methodology to other products, and then to services also. We have got our target to achieving generality in combining numerical and semantic processing of diversified data describing various aspects of some product or services.

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