A GAMIFICATION APPROACH FOR THE IMPROVEMENT OF PAID CROWD-BASED LABELLING OF GEOSPATIAL DATA

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ABSTRACT:

Non-commercial, unpaid crowdsourcing is the basis of many non-profit projects on the Internet such as Wikipedia or OpenStreetMap. A prerequisite for such projects to be successful is to find a sufficient number of volunteer crowdworkers who are intrinsically motivated to participate. In the field of geodata collection, many tasks exist that in principle could be solved with crowdsourcing; however, finding a large number of volunteers is problematic. There is also paid crowdsourcing in addition to crowdsourcing based on voluntary collaboration. The main incentive for participating in paid crowdsourcing projects is primarily payment for the work. Thus, intrinsic motivation is replaced by extrinsic motivation. However, intrinsic motivation simply replaced by extrinsic motivation can lead to a reduction in performance. If there are no additional intrinsic incentives in addition to monetary payment, it can happen that crowdworkers only perform exactly as much work as is necessary to satisfy the employers. Gamification may positively influence the motivation of paid crowdworkers. The goal of this paper is to investigate whether it is possible to increase the performance of paid crowdworkers with gamification. To this end, we have developed a web-based tool for the labelling of 3D triangle meshes. We presented this tool with and without game elements to paid crowdworkers and investigated to what extent gamification influenced the quality and quantity of the collected data.

1. INTRODUCTION

The term *Crowdsourcing* was coined by Jeff Howe (Howe, 2006) and is a neologism consisting of *crowd* and *outsourcing*. Unlike outsourcing, where employers outsource tasks to known and well-defined third parties, crowdsourcing outsources tasks to unknown workers (crowdworkers) on the internet. There are many non-profit crowdsourcing projects that rely on the work of unpaid volunteers, such as Wikipedia (www.wikipedia.org), or Zooniverse (www.zooniverse.org).

The collection of geospatial data by volunteers is known under the term Volunteered Geographic Information (VGI) (Goodchild, 2007). The most popular VGI project is OpenStreetMap (OSM) (www.openstreetmap.org), an open collaborative project to create a detailed map of the world that can be edited by anyone (Haklay and Weber, 2008). Besides OSM, numerous other VGI projects exist. An overview can be found in (Sui et al, 2013).

Crowdsourcing projects that are based on the work of unpaid volunteers need an active community whose members are convinced about the importance of these projects and who have an intrinsic motivation to collaborate. This can only be realized for some applications. In the field of geodata collection, many tasks exist that in principle could be solved with crowdsourcing. However, finding a sufficiently large number of volunteers can be difficult in this case. This particular problem is encountered especially when the produced results are not made available under a Creative Common Licence, as in OpenStreetMap. Other incentives must be provided to motivate crowdworkers to participate in these projects.

The most common extrinsic motivation for crowdworkers that leads to the fastest results is getting paid for the work (Haralabopoulos et al., 2019). In paid crowdsourcing, tasks are published on online marketplaces that are responsible for recruiting and paying the crowdworkers. The workers are financially compensated for completing tasks (Mao et al., 2013). Established marketplaces such as microWorkers (www.microworkers.com) (Hirth et al., 2011) or Amazon Mechanical Turk (MTurk - www.mturk.com) (Ipeirotis, 2010) can draw on a large pool of potentially interested crowdworkers. For example, microWorkers has access to more than 2,700,000 crowdworkers worldwide (according to their website - accessed March 2022).

Paid crowdsourcing has proved to be a powerful tool for very diverse applications. It can be used for practically any task that can be performed online by using a computer; and it has also been successfully applied for the collection of spatial data: Estes et al. (2016) describe a platform for the mapping of crop fields in South Africa realized with Mechanical Turks' Human Intelligence Tasks (HITs). Walter and Soergel (2018) discuss the collection of buildings, forests and streets from aerial images with the help of microWorkers campaigns. Walter et al. (2020) examine the collection of trees from 3D LiDAR point clouds based on paid crowd campaigns. Maddalena et al. (2020) implemented a system to collect coordinates of points of interest from Street View images with paid crowdworkers. Koelle et al. (2021b) evaluated which 3D data representation (point cloud vs. mesh) is best suited for presenting to paid crowdworkers. Walter et al. (2021) present a two-level approach for the collection of vehicles from 3D point clouds by paid crowdworkers.

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Paid crowdsourcing also has its limits: One major problem is lack of motivation of the crowdworkers. Paid crowdworkers can be seen as *satisficers* (a neologism of *satisfying* and *suffice*) that are characterized by doing only the minimal work necessary to satisfy the employer (Chandler et al., 2013). This lack of motivation can lead to low quality results in paid crowdsourcing (Fleischer et al., 2015; Cheung et al., 2017). The focus of paid crowdworkers is often primarily on getting paid, which is why it can so happen that they put as little effort as necessary into completing tasks (Chandler et al., 2013).

The idea we explore in this paper is whether gamification can be used to increase the motivation of paid crowdworkers. We hope that this will lead not only to better data quality but also to more data being collected for the same salary.

Deterding et al. (2011) define gamification as the use of game design elements in non-game contexts. Gamification can be beneficial because introducing game elements makes people more likely to do work without the need for extrinsic rewards (Martella et al., 2015). The main goal of gamification is to increase human motivation and performance in relation to a specific activity (Sailer et al., 2017). Monotonous activities can be made more interesting by introducing game elements into them (Sailer et al., 2013). The activities should be fun and rewarding, which in turn should stimulate users to 'keep playing' (Franga et al., 2015).

Gamification can be seen as an attempt to redirect crowdworkers' motivation from the purely rational pursuit of profit to a self-interested, intrinsically motivated activity (Morschheuser et al., 2017).

Crowdsourcing tasks can be "gamified" by adding game elements to the actual crowd job (Chamberlain et al., 2013). In two experiments, it was shown that the combination of gamification and paid crowdsourcing makes it possible to reduce costs for the employer through voluntary extra work (Lichtenberg et al., 2020) and to increase the quality of the results for the same pay (Feyisetan et al., 2015). Both experiments were performed on non-spatial tasks: In Lichtenberg's experiment, crowdworkers had to place various sliders on specific positions; in Feyisetan's experiment, crowdworkers had to label images. To our knowledge, the combination of gamification and spatial data collection by paid crowdworkers has not been investigated yet.

Several studies (Matyas et al., 2011; Martella et al., 2015; Bayas et al., 2016) examine the use of gamification for the collection of geospatial data by volunteer crowdworkers. Naturally, it is more difficult to motivate paid crowdworkers with gamification than motivating volunteer crowdworkers, since paid crowdworkers perform crowd jobs to earn their living whereas this is not the case for volunteer crowdworkers.

In this paper, we investigate the impact of gamification on paid crowdsourcing on the example of labelling triangles of a 3D triangle mesh. In particular, we investigate whether gamification motivates paid crowdworkers to voluntarily label more triangles and whether greater accuracy can be achieved.

The remainder of this paper is organized as follows. The data used in this research are described in section 2. In section 3, we present the graphical user interface for the labelling of triangles and in section 4 we discuss the game elements used. The crowdsourcing campaign parameters are presented in section 5. In section 6, we discuss the results of an initial test. A detailed study of the reproducibility of the results of this initial test is given in section 7. After a conclusion and a discussion of the limitations of our approach, the final section provides an outlook for future work.

2. TEST AREA

As test area, we relied on the newly introduced Hessigheim 3D benchmark dataset (H3D) and focus on epoch March 2018 (Koelle et al., 2021b). Hessigheim is located in the southern part of Germany. The point cloud was collected with a RIEGL VUX-1LR LiDAR sensor combined with two Sony Alpha 6000 oblique cameras using the RIEGL RiCopter platform. The mean laser pulse density is 300-400 points/m² per strip and more than 800 points/m² for the entire flight block due to the nominal side overlap of 50%. The ranging accuracy, reported in the data sheet of the sensor is 10 mm (Riegl, 2018).

A textured triangle mesh was computed using both LiDAR data and imagery. For testing our approach, a square section of size 50 m × 50 m was chosen, which consists of about 50,000 triangles. Figure 1 shows an overview of the test area and Figure 2 shows an enlarged section in which the triangles are visible.

Figure 1. Overview of the test area (size 50 m × 50 m, approximately 50,000 triangles).

Figure 2. Enlarged section of the test area.

We needed reference data to evaluate the outcome of crowdworkers during labelling to calculate simultaneously a game score. To this end, 25 triangles each were selected for seven different land use classes: [1] Grass or Dirt, [2] Street, [3] Vehicle, [4] Roof, [5] Facade, [6] Vegetation, [7] Other. We chose the triangles at random, but made sure that we only used those that could be clearly classified, so that the results were not biased by triangles that might be ambiguous with respect to their class affiliation (e.g., triangles situated directly on class borders). For each crowd job, 20 of the 175 triangles were randomly selected. If a crowdworker worked on several jobs in succession, new triangles were selected for each job. A crowdworker would have to run at least nine jobs in a row to see the same triangles twice - which did not happen in our tests.

3. GRAPHICAL USER INTERFACE

The success of a crowdsourcing campaign depends on the qualification of the crowdworkers and also on the design of the tools used (Feyisetan et al., 2015; Kittur et al., 2013). For this reason, the graphical user interface should be easy to use and have an appealing design. In the following, we explain how the labelling tool works.

The crowd job starts with two introductory pages that explain what the crowd job task is and how to use the graphical user interface (see Figure 3; note that the text in white colour is hard to read in the printed version - but when displayed on a monitor, the text is clearly visible). In the first introductory page, crowdworkers see the note "make sure to label the faces correctly as too many incorrect faces can influence your payment". In fact, we did not perform this check. However, it has been shown that the announcement of such a test alone increases the quality of the results (Suri et al. 2011).

Figure 3. Introduction pages explaining the crowd job.

For each crowd job, 20 triangles are selected one after the other from the 3D triangle mesh and shown to the crowdworkers. The task of the crowdworkers is to label the triangles.

Figure 4 shows the graphical user interface on an example during labelling. The 3D triangle mesh is presented to the crowdworkers without lines to provide a smoother image that allows easier interpretation for non-experts. The triangle mesh is automatically rotated and zoomed in real-time until the triangle to be labelled is visible. The triangle is highlighted and the crowdworkers can select the land use class from a list of seven entries.

After labelling one triangle, the next triangle is automatically selected and the triangle mesh is again rotated and zoomed in real-time so that the triangle to be labelled gets visible. After all triangles have been labelled, the crowdworkers have the option to repeat the crowd job (see Figure 5).

Figure 4. Labelling of one triangle.

Figure 5. After completing a crowd job, the crowdworkers are asked if they want to repeat the job.

4. GAMIFICATION ELEMENTS

To assess the impact of gamification, a second graphical user interface was developed with the following additional game elements:

- A progress bar shows the percentage of triangles that have already been labelled (see Figure 6).
- A final score shows the number of correctly labelled triangles after completion of the crowd job (see Figure 7). If the crowdworkers are not satisfied with their result, they can repeat the crowd job.
- After the crowd job is finished, a high score list with worker IDs is presented (see Figure 8).
- Audio-visual effects: In addition to background music, visual and audible effects have been introduced to provide feedback during labelling on whether a triangle has been labelled correctly or not. If a triangle is labelled correctly, a pleasant tone sounds and the screen briefly turns green. If a triangle is labelled incorrectly, an unpleasant tone sounds and the screen briefly turns red.

All game elements used in this paper are very typical for games and are often used in the context of gamification (Sailer et al. 2013). A list of further possible game elements can be found in (Deterding et al. 2011).

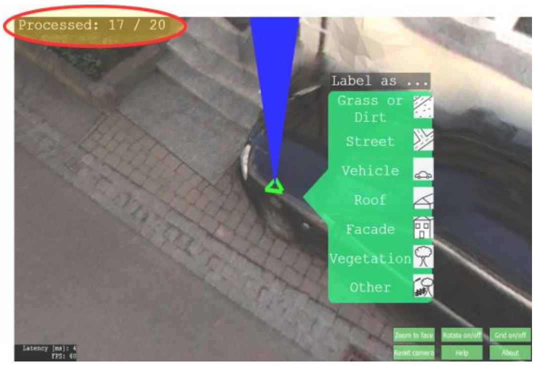

Figure 6. A progress bar shows how many triangles have already been labelled.

Figure 7. After completion of the crowd job, the number of correctly labelled triangles is displayed.

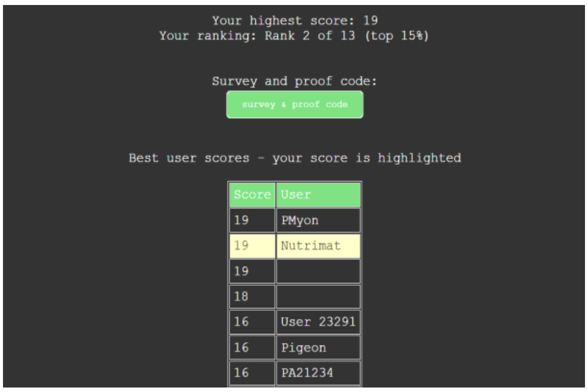

Figure 8. High score list with worker IDs.

5. CAMPAIGNS

For the following studies, 90 crowd jobs were combined into one campaign each. All campaigns were executed on microworkers.com and defined in the same way:

- All task descriptions were identical
- All crowd jobs were offered to the same group of crowdworkers (microWorkers group *international workers*)
- All campaigns were started at the same time
- All crowd jobs were paid identical amounts

We paid \$0.10 per crowd job. For each campaign, an additional 10 per cent of the cost was paid to microWorkers. Thus, the total cost per campaign was 90 × \$0.10 × 1.1 = \$9.90.

Table 1 shows the distribution of origins of the crowdworkers who participated in this project, sorted by the top 10 countries. The top three countries are Bangladesh, India, and the Philippines. These are all countries where average salaries are typically rather low.

Country	Percentage of Crowdworkers
Bangladesh	53.0
India	9.5
Philippines	8.4
Serbia	3.1
Brazil	2.5
Venezuela	2.1
Bulgaria	1.3
Pakistan	1.3
Colombia	1.1
United States	1.1

Table 1. Distribution of origins of the crowdworkers sorted by top 10 countries.

6. FIRST RESULTS

For the evaluation of the results, we measured two values per campaign: (i) average number of labelled triangles per crowdworker = sum of all labelled triangles / number of crowdworkers and (ii) correctness = (number of correct labelled triangles / number of labelled triangles) × 100.

In a first test we evaluated two campaigns: one with and one without gamification. Table 2 shows the results of this test. It can be seen that gamification has increased the average number of labelled triangles per crowdworker by a factor of about 2.5.

Interestingly, even without gamification, more triangles were labelled than minimally necessary, since only 20 triangles must be labelled per crowd job. An average of 26.6 triangles were labelled per crowdworker in the campaign without gamification. This means that even without game elements, about 50 per cent of the crowdworkers tried to improve their results by repeating the crowd job. An explanation for this might be that some crowdworkers want to make sure to get full payment and try to deliver good results in order to receive a good rating from the employer.

Campaign	Average number of labelled triangles per crowdworker	Correctness
Without gamification	26.6	74.5%
With gamification	73.3	72.9%

Table 2. Results of two campaigns without and with gamification.

The correctness did not increase due to the use of gamification, but actually decreased slightly from 74.5% to 72.9%.

The average cost per triangle for the campaign without gamification is \$9.90 / (26.6 × 90) = 0.41 cents and for the campaign with gamification is \$9.90 / (73.3 × 90) = 0.15 cents.

7. REPRODUCIBILITY

The results presented in section 6 are promising, but to what extent these results can be reproduced remains an open question. While we need to investigate whether the same results can be achieved with a different group of crowdworkers, it is also necessary to investigate whether a habituation effect does set in, which might lead to a decrease in improvement due to gamification when the same crowdworkers perform the crowd jobs multiple times. For this reason, we conducted two more studies. In the first study (A), we repeated the two campaigns of the first test three times with 90 crowdworkers each (2 × 3 × 90 = 540 crowd jobs). In the second study (B), we repeated the two campaigns described in the first test again three times with 90 crowdworkers each, but now allowing only those crowdworkers who had not worked on any other crowd job in this project before. This means that in study A, a crowdworker can work on several crowd jobs, while in study B, each crowdworker is only allowed to work on one such job and is not allowed to work on any other crowd job.

7.1 Study A (Crowdworkers can work on several Jobs)

For the 540 crowd jobs in study A, 241 crowdworkers were registered. Of them, 115 performed one crowd job each and 126 crowdworkers performed two or more crowd jobs each. On average, one crowdworker performed approximately 2.24 crowd jobs.

7.1.1 Labelling without Gamification

Table 3 shows the results of labelling without gamification. The results are relatively stable. The average number of labelled triangles per crowdworker varies between 25.1% and 26.6%. The correctness varies between 74.1% and 75.1%.

Campaign	Average number of labelled triangles per crowdworker	Correctness
A1	26.6	74.1%
A2	26.6	75.1%
A3	25.1	74.1%

Table 3. Results of labelling without gamification in study A.

7.1.2 Labelling with Gamification

Stronger differences can be seen in the campaigns with gamification (see Table 4). The average number of labelled triangles per crowdworker decreases significantly and the correctness increases slightly as the number of campaigns increases. In the third campaign (AG3), almost only half of the triangles were labelled compared to the first campaign (AG1).

Campaign	Average number of labelled triangles per crowdworker	Correctness
AG1	54.4	66.8%
AG2	45.5	71.3%
AG3	30.8	73.5%

Table 4. Results of labelling with gamification in study A.

For further examination of these numbers, the crowdworkers were divided into two groups: (i) the crowdworkers who performed only one crowd job (one-time crowdworker) and (ii) the crowdworkers who performed two or more crowd jobs (multi-time crowdworker). Table 5 shows the distribution of these two groups.

Campaign	One-time crowdworker	Multi-time crowdworker	Total
AG1	22	68	90
AG2	17	73	90
AG3	14	76	90

Table 5. Number of crowdworkers in study A.

The number of one-time crowdworkers decreases and that of multi-time crowdworkers increases as the number of campaigns increases. The decreasing average number of labelled triangles per crowdworker can be explained with a habituation effect that occurs among the mutli-time crowdworkers. This relationship is illustrated in Figure 9: a larger amount of one-time crowdworkers leads to a larger average number of labelled triangles per crowdworker, while a smaller amount of one-time crowdworkers (and thus a higher amount of multi-time crowdworkers) leads to a smaller average number of labelled triangles per crowdworker.

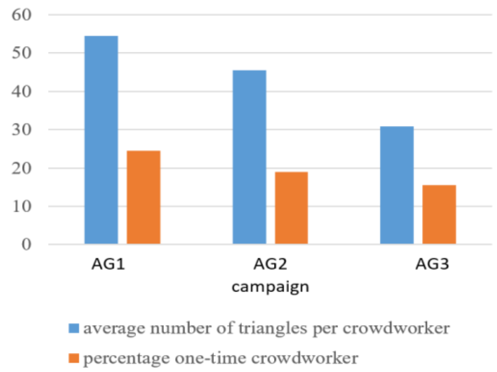

Figure 9. Average number of labelled triangles per crowdworker compared to percentage of one-time crowdworkers.

As the number of campaigns increases, less voluntary extra work is performed which leads to the conclusion that the gamification elements lose their appeal. Using the example of a leader board, this could mean that crowdworkers who had already achieved a good ranking in a past campaign could only be slightly motivated again by a leader board.

In addition to the decrease in the amount of data collected, an increase in correctness can be observed (see Table 4). This can be explained in the light of experience gained by multi-time crowdworkers. If a crowdworker has already worked on a crowd job within the scope of this project, he has gained experience with the labelling tool. The task that the crowdworkers have to work on is actually not difficult (see detailed description in section 3). However, the interpretation of the textured mesh is difficult at first for crowdworkers who have never seen such data (and this is probably the case for most of them). However, this becomes easier with repeated processing of the data. Figure 10 shows this correlation between correctness and number of multi-time crowdworkers.

7.2 Study B (Crowdworkers work on one Job only)

A total of 540 crowd jobs were evaluated in study B. Of them, 270 (3 campaigns with 90 crowd jobs) were offered without game elements (campaigns B1, B2, and B3) and the other

270 jobs (3 campaigns with 90 crowd jobs) with game elements (campaigns BG1, BG2, and BG3). In contrast to study A, only crowdworkers who were not involved in any other campaign within the scope of this project were admitted.

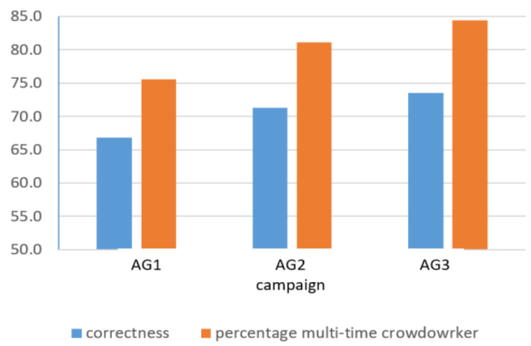

Figure 10. Correctness compared to percentage of multi-time crowdworkers.

7.2.2 Labelling without Gamification

Table 6 shows the results of labelling without gamification. The average number of labelled triangles per crowdworker is around 30 for all three campaigns, which is slightly higher than the corresponding campaigns in study A, because no multi-time crowdworkers participated at all. The average correctness is slightly lower for the same reason.

Campaign	Average number of labelled triangles per crowdworker	Correctness
B1	33.5	65.6%
B2	30.0	73.6%
B3	30.2	65.1%

Table 6. Results of labelling without gamification in study B.

7.2.2 Labelling with Gamification

Table 7 shows the results of labelling with gamification. Since there were no crowdworkers who had already worked on other crowd jobs in this project, no habituation effect of the game elements occurred and no reduction in the average number of labelled triangles per crowdworker could be observed. Compared to Table 6, the average number of labelled triangles per crowdworker is significantly higher because all participants are one-time crowdworkers. The correctness could not increase as no mutli-time crowdworkers participated in the campaigns.

Campaign	Average number of labelled triangles per crowdworker	Correctness
BG1	58.8	62.6%
BG2	73.1	68.9%
BG3	63.3	67.2%

Table 7. Results of labelling with gamification in study B.

7.3 Campaign durations (Studies A and B)

A significant difference between studies A and B arises when considering the required times to complete the campaigns. Table 7 shows the campaign durations of the two studies without gamification (1, 2, 3) and with gamification (G1, G2, G3). The campaigns of study B, where each crowdworker was only allowed to perform exactly one crowd job, took significantly more time than the campaigns of study A, where a crowdworker was allowed to perform several crowd jobs. In study B, it can also be seen that the campaign duration increases in tandem with the campaign number.

Campaign	Study A	Study B
1	3.4 h	6.7 h
2	1.5 h	24.6 h
3	2.1 h	64.1 h
G1	2.8 h	13.4 h
G2	1.6 h	18.1 h
G3	1.9 h	41.9 h

Table 8. Campaign durations.

The reason for the longer campaign duration in study B is that we need significantly more different crowdworkers to complete all crowd jobs, since in study B each crowdworker is only allowed to work on exactly one job. Study A involved 241 different crowdworkers (see Section 7.1), while study B involved 540 different crowdworkers. The supply of available crowdworkers on mikroworkers.com is not large enough to meet this increased demand without resulting in longer campaign times.

8. CONCLUSIONS

The goal of combining crowdsourcing and gamification can be either to increase the quality of the collected data or to motivate the crowdworkers to collect more data for the same payment. More collected data also means lower cost. From an ethical point of view, the question arises whether this is a desirable approach at all, especially in the context of workers coming from rather poor countries. To answer this question, however, many other aspects have to be considered, such as the average income in the respective country or how work satisfaction is defined. However, due to the limited space available, we cannot discuss these aspects adequately here and will therefore limit ourselves to the technical aspects.

We were able to show that crowdworkers could be motivated to collect significantly more data with gamification compared to crowdworkers who performed the same tasks without gamification. However, we found that this effect decreased for crowdworkers who performed tasks multiple times.

In order to avoid a habituation effect, crowd campaigns can be carried out in such a way that each crowdworker is not allowed to perform several crowd jobs, but each job is assigned to a different crowdworker. However, the problem is that this leads to significantly longer campaign durations. The crowdsourcing marketplace microworkers.com used in this project has over 2.7 million registered crowdworkers (according to their website, retrieved March 2022). However, only a fraction of these crowdworkers were indeed available. Either they were no longer actively working or they were not interested in our tasks. For this reason, the approach of allowing crowdworkers to perform only one crowd job has limited scalability. For larger data collection tasks, there would not be enough crowdworkers to complete a project within an acceptable time.

Improvements in the quality of the collected data through the use of game elements could not be demonstrated. The quality of the crowd jobs without game elements and the crowd jobs with game elements did not differ significantly. However, it was found that crowdworkers who performed crowd jobs multiple times achieved greater quality. However, this effect is independent of the use of game elements, but can be attributed to the fact that crowdworkers who perform crowd jobs multiple times achieve greater experience with the labelling tool.

For the realization of gamification, it is necessary to give feedback to the crowdworkers immediately after they have input their data, so that they can directly determine how well they have worked. This is easy to realize when measuring the number of labelled triangles, but difficult when evaluating the correctness of the labelled triangles, as we need reference data for this.

In our case, we collected reference data ourselves to evaluate correctness. Normally, we have no reference data available; otherwise it would not be necessary to collect the data with crowdsourcing. A possible solution would be to collect only part of the data as reference and then evaluate only some of the data input of the crowdworkers. It would also be conceivable to at least roughly estimate the quality of the crowd results with the help of automatic semantic segmentation algorithms.

Both techniques can be combined: control tasks for part of the crowd jobs for which reference data are available and a rough assessment of the quality of the results in between. However, this would lead to the fact that only a part of the data inputted by the crowdworkers is evaluated and the feedback to the crowdworkers becomes blurred. This would dilute the gamification effect.

9. LIMITATIONS

We tested our method in an initial test with 180 crowd jobs and in two follow-up studies with an additional total of 1080 crowd jobs. Almost 1000 different crowdworkers participated in this research. We chose such a high number of participants to ensure that the results are statistically meaningful. However, these results are closely related to the crowdsourcing marketplace used. All campaigns were conducted on mircoWorkers. It is conceivable that different results would emerge if we switched to a different crowdsourcing marketplace with a divergent pool of workers with different skill sets (e.g., most workers on Amazon Mechanical Turk are U.S. citizens, while workers on microWorkers are predominantly based in Asia).

10. FUTURE WORK

The game elements used in this work are relatively simple (progress bar, score, high score list, and audivisual effects). Nevertheless, we were able to show that they had a significant impact on the crowdworkers, although the effect lasted only for a limited time. Also, there are many other game elements that could be used, such as storytelling, virtual worlds, avatars, trophies, team tasks, strategy, rewards, social networks, competition, Easter eggs, quests, levels, etc.

It could be possible to achieve stronger gamification effects if we develop data collection tools with more complex game elements. We will investigate this in our future work. Incidentally, it must be kept in mind that the development of an attractive game is a very tough task that cannot be performed easily.

It is more difficult to motivate paid crowdworkers with gamification than to motivate volunteer crowdworkers with it, since paid crowdworkers often do the work to earn their living, which is not the case for volunteer crowdworkers. One way to enhance the effect of gamification for paid crowdworkers would be to link the payment to the game score, providing an additional extrinsic motivation for crowdworkers. This will be also part of our future research.

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