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A literature review of Empirical Evidence on Procedural Content Generation in Game-Related Implementation

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Abstract. Procedural Content Generation (PCG) is an emerging field of study in computer science that focuses on automating the process of generating content by using algorithm, reducing human workload with less human interference by automating the process. Generally speaking, the application of PCG has been adapted in multiple form of contents, especially computer games. However, a more specific empirical evidence on how it is being used in a game-related implementation are still scarce. This paper presents the findings of review performed in the past 5 years, looking on how PCG are being applied in game-related content. The studies had shown that PCG are being used extensively in game-related content but has seen more uses on specific type of contents rather than being used for the entire game content. Result shows that there are no single best type of PCG method or algorithm, but instead a combination of multiple approaches based on what content is being generated. Result also shown that PCG are being used in multiple type of games, however, based on the paper found, only certain types of game benefits PCG extensively such as action and platforming games, while other model and genre of games have not seen much PCG application yet. Further studies are also required to analyze how experimentation and evaluation of PCG are being done as well as PCG domain in educational games as well as game-based learning, the quality characteristic being analyzed on the papers are also worth mentioning to understand the underlying result of PCG usage in game-related contents.

Keywords: *Procedural content generation, serious games, literature review, empirical evidence, content generation*.

1 Introduction

Digital games have become an interesting topic in the recent years [1], [2]. The untapped potency of such digital games is massive, the inherent flexible nature of digital games allows it to convey various messages encompassing multiple disciplines of knowledge [3]–[6]. As technology develops, so does the average computational power of computers [7], this is crucial for the computer usage in the sense of processing speed, capacity of data being processed, and optimization of such process.

Based on the current state of digital games and its nature, as well as unfathomable speed of how computation power is being developed, the development of game contents is moving at similar pace as well [8]. Conventional content generation in digital games is a very rigorous and time-consuming process [9], much of its development pipeline requires multiple parts of development lifecycle and requires multiple expert to validate its output [10].

However, with the increase of computational power of computers, an automated process of generating content for digital games emerges, allowing little to no human intervention or interference on the process of generating such contents [11]. The means of generating content in digital games requires a set of rules that is defined in a form of algorithm [12], such field is called "procedural content generation" or often abbreviated as PCG [13]. As the name suggests, contents are generated procedurally instead of randomly generation with little to no pattern.

The usage of PCG is pervasive in modern digital games development, multiple games for entertainment purpose uses procedurally generated content in form of map generation [14] for strategy games [15] as well as generating enemy's formation on role-playing games (RPG) [16]. A procedurally generated gameplay area also made by using similar method for puzzle games [17]. In fact, the usage of PCG in game development is ubiquitous, not using such method for large-scale games may either be considered a true work of artisanal experts [18], or a bad practice of game development life cycle.

However, the usage of PCG on digital games in form of serious games are far less documented. Several studies in form of collective and comprehensive details on PCG has already been done [13], another study has also been done to identify some empirical evidence on how PCG is used in games in general [19] as well as a study focusing on its usage in term of game development [20], however the studies done are far too broad while the existing literature review are more on a generic point of view, furthermore, the existing studies that has been done are quite outdated as it is mostly published more than 5 years ago.

The domain of PCG is an interesting area in the field of artificial intelligence in game as well as evolutionary computing in general [21], multiple researches on the optimization and usage potency of PCG on multiple fields has already existed– be it related to game or not [22]–[25], yet researches on such topics in serious games context in form of PCG application are still scarce.

This study aims to address the status quo of PCG usage in serious games, focusing on multiple aspect of PCG as well is how it is implemented, evaluated, and to what kind of games it is implemented on. The contributions of this paper includes: (i) reviewing and eliciting relevant information and inferences regarding the issue on such domain, (ii) providing quick reference on the domain of research being reviewed, and (iii) providing empirical evidence on PCG usage in serious games.

2 Methodology

The methodology of this research starts with the definition of limitations and constraints of this study which is used to explicitly shows the limitation of this study from multiple perspective, the definition of constraints also shown here to further shows what specific phase or action that cannot been done during the research due to some reasons, then, a set of research question formulation to gather relevant information, a definition of search term in order to gather the information specifically related to PCG, determination of online database to elicit such information, filtration and scoping to filter the gathered papers, inclusion criteria in which it will be used to determine which paper will be added to the research and which ones that aren't, and lastly the data analysis visualization method, to create an easier more understandable result.

2.1 Limitations and Constraints

The limitations of this study are that the researches taken into consideration is limited to the papers that are released in journals and conference proceedings between the year of 2014 to 2018. This study limits the results into two categories which are (1) based on its overview characteristic such as source, years, paper type, and research levels and (2) based on its PCG implementation (work type, focused content, method/algorithm/approaches, game models and game genre). Based on its explanation of results, this study limits the amount of papers being listed in each subsection of the result for the sake of easier general understanding as the paper aims to show a general understanding in a form of systematic literature review.

The constraints of this study are that some online databases are only able to process limited length of search term strings, as such, the search term is the limited based on the online databases capability. This study also limits the contribution of research into a somewhat basic overview of PCG and its implementation, as such, the results subsection as shown on the limitation above is limited to only the said subsections

2.2 Research Question Formulation

In order to elicit relevant information on the current condition of PCG usage in serious games, several research questions are defined. The research questions are listed down below:

RQ1: How does the of existing researches are being distributed based on its source?

RQ2: How does the of existing researches are being distributed based on the year it was published?

RQ3: How does the of existing researches are being distributed based on its paper type?

RQ4: How does the of existing researches are being distributed based on its research level?

RQ5: What type of work are being researched based on the existing researches?

RQ6: What content being focused are being researched based on the existing researches?

RQ7: What kind of method, algorithm, and approaches are being researched based on the existing researches?

RQ8: What game models are being implemented with PCG based on the existing researches that focuses on serious games?

RQ9: What game genre are being implemented with PCG based on the existing researches that focuses on serious games?

2.3 Search Term Definition

The search terms are derived from contents that generally generated from a PCG process (A1), combined with a context of serious games (A2), an additional search term to focus on implicative and associative contents (A3) are also added to increase the focus of the papers searched. There exist two types of PCG related search term as several search engines from the online databases are only able to process limited amount of strings, while stronger search engines use the longer search term.

PCG process-related search term (A1v1)

((((((((((procedural AND generation) OR procedural AND world AND generation) OR procedural AND content AND generation) OR procedural AND map AND generation) OR procedural AND level AND generation) OR procedural AND terrain AND generation) OR procedural AND feature AND generation))

Alternative PCG process-related search term (A1v2)

((procedural AND generation) AND (content OR world OR map OR level OR terrain OR feature))

Serious games-related search term (A2)

(((serious AND games) OR online AND games) OR video AND games))

Focusing search term (A3)

((((((((((((factor OR link) OR elements) OR features) OR characteristic) OR attributes) OR control) OR curiosity) OR empirical) OR evidence) OR research) OR data) OR school)).

2.4 Determining Online Databases

Online database that is used on this research are Science Direct, IEEE Xplore, ACM Digital Library, ERIC, and Springer Link.

2.5 Filtering and Scoping

Filtering is done to filter the papers searched by certain criteria. The papers are first filtered by its year into the last 5 years counting from 2018, then the papers are filtered if any duplicate exist. The paper is then scoped based on relevant research questions and processed based on aforementioned categories of research questions.

2.6 Inclusion Criteria

Any included papers are then reviewed manually and selected to be relevant with the search term and research questions, the papers included on this research needs to some extent focuses on PCG at the very least. Other more advanced criteria may include PCG application on serious games or education-related game implementations.

2.7 Data Analysis and Visualization Method

Data analysis method used on this research are generic form of descriptive statistics, represented in tabular forms. Visualization method used on this research are simple charts such as bar chart, line graph, and pie chart.

3 Results

3.1. Main Selection Process

1. Papers identified by search term

Based on the search term, a grand total of 3.159 papers has been identified by using the first search term filter, however, after the second search term filter, the number goes down to 371 and goes down again into 279 by the last search term filter. Table 1 depicts the total of papers identified by its search term based on its source of online database and its filter. Several online databases are unable to process too many strings thus are labeled with an asterisk symbol (*).

Table 1. Total number of papers identified by search term

Online Database Searched	Papers Identified		
	A1	***A2***	***A3***
Science Direct	47	47*	47*
IEEE Xplore	162	50	41
ACM Digital Library	2875	213	130
ERIC	15	15	15
Springer Link	60	46	46*
Total	3159	324 + 47*	186 + 93*
Grand Total	3159	371	279
**) Search term too long*			

2. Papers filtered using filtering and inclusion criteria

Filtering and inclusion criteria are then applied into the final 279 papers done by previous steps, this includes manual filtering by using the papers' abstract and introduction, the process checks the fitness of such paper manually, and by detecting any duplicates or versions filter based on its criteria applied. Table 2 depicts the total papers filtered and included as the final amount of papers processed in this study, a grand total of 78 papers has been filtered by using the filtering and inclusion criteria.

Table 2. Total number of papers filtered using filtering and inclusion criteria

Online Database Searched	Manual Filtering	Duplicate/ Version Filter Inclusion Criteria Applied
Science Direct	23	7
IEEE Xplore	32	24
ACM Digital Library	53	43
ERIC	1	1
Springer Link	6	3
Total	115	78

3.2. Overview

In the overview, the 78 papers searched are then identified by using its sources, year published, paper type, and its research level. The result of this process is meant to show an empirical proof of the observation related to papers basic identifiable features.

1. Source

This part of the result sub-chapter answers RQ1: How does the of existing researches are being distributed based on its source?

Based on its source, a clear trend are shown by several online sources that focuses on technical-heavy materials and focusing more on algorithm such as IEEE Xplore and ACM DL which taken more than three quarter of the total paper in this study, as depicted on table 3, other online sources shows less focus on PCG in general, this shows a clear trend of PCG algorithmic and technical nature compared to its implemented and implicative aspect

2. Years

This part of the result sub-chapter answers RQ2: How does the of existing researches are being distributed based on the year it was published?

Based on its year published, there is a very clear trend of PCG as a growing domain of interest with a steady growth of research being done by researchers around the world focusing on PCG, there is a clear result shown by Figure 1 that depicts such growth in the past 5 years of study. As per previous sub-chapter, technical-heavy online sources show a clear lead with the amount of research done in the past 3 years.

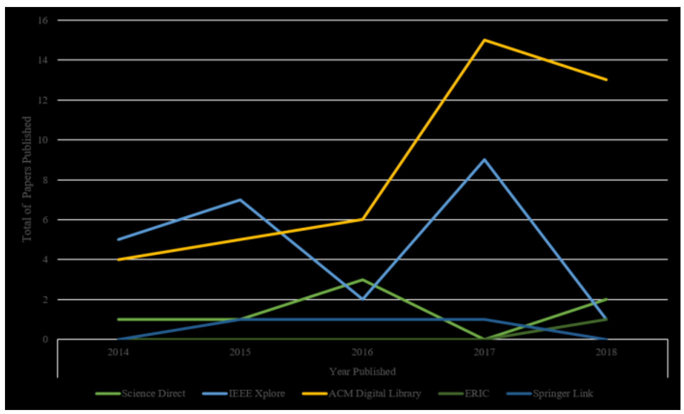

Figure 1. Total number of papers published based on its year published.

3. Paper Type

This part of the result sub-chapter answers RQ3: How does the of existing researches are being distributed based on its paper type?

Based on its paper type, an interesting result are founded related to previous sub-chapter of source, around 70% of the total papers used on this study are in a form of conference proceeding, implying that PCG is a new and growing field of study with a very large potency lies behind it. ACM DL shows a massive difference between the amount of conference proceeding compared to journals used on this study, while IEEE Xplore shows a much more balanced amount of paper types, on the other hand, other online sources show a clear amount of evidence of a more complete work in form of journals. As being shown on Figure 2, the distribution of journals on this study are evenly distributed.

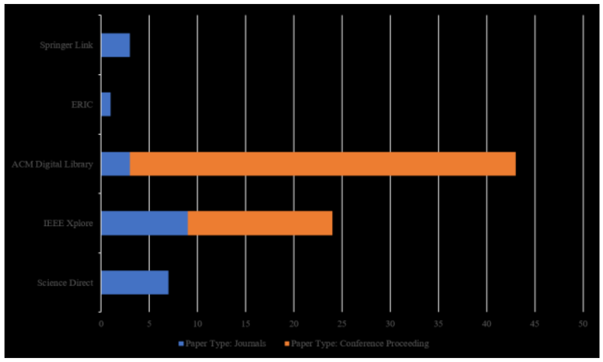

Figure 2. Total number of papers based on its paper type.

4. Research Level

This part of the result sub-chapter answers RQ4: How does the of existing researches are being distributed based on its research level?

The research levels are used to show to what extent the state-of-the-art researches are being done in the field of PCG are being done. As well as understanding the level of research is needed to reach a certain type of paper publication. Based on the result shown on Figure 3, a vast majority of the papers are categorized as a tested result, while it is not impossible to simply formalize an idea and use it as a proper research idea, or in a form of prototypes.

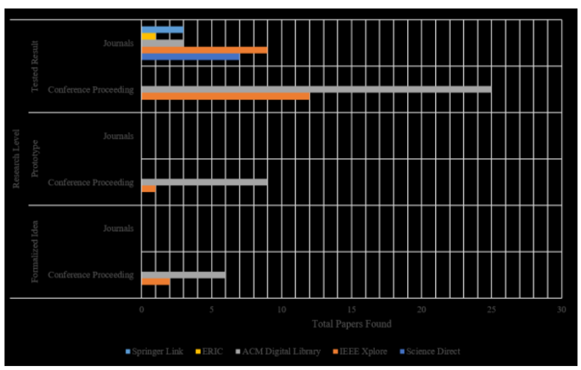

Figure 3. Total number of papers based on its research level.

3.3. Procedural Content Generation (PCG)

On this research, PCG is defined as “the algorithmic creation of game content with limited or indirect user input” based on [26]. The term “content” in PCG are defined as anything that exist and contained in a game, which includes levels, maps, game rules, etc. [13], while the term game is more strictly defined and categorized narrowly into digital games.

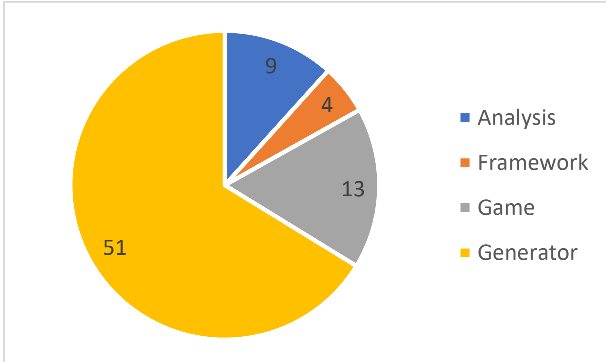

Figure 4. Total number of papers based on its PCG work type.

1. Work Type

This part of the result sub-chapter answers RQ5: What type of work are being researched based on the existing researches?

PCG work types are defined as the types of work being done by using PCG as a means of delivery. The work types are divided into 4 categories: (i) analysis, (ii) framework, (iii) game, and (iv) generator.

Analysis work type focuses only on the analysis aspect of any existing PCG method or analyzing a comparison between different method of PCG. Analysis work type focuses more on planning, assessment, commentaries, or a planned model. This work type category does not include any form of developed framework or developed content or creation of a new content or new form of PCG.

Framework work type extends the analysis work type with a theoretical and planned model along with an elaboration of such plan. However, this work type does not create an entire game nor shows a generated content that is measurable as there is no content being created to be measured. This work type nor does the work type also does not intend to continue its work into a fully working game, but instead only a fraction of the game or a part of an existing game.

Game work type further extends the framework work type by using PCG to generate an entire game as a generated content. This work type does not include work type that generates contents of a game, but focused more into works that creates an entire game by using PCG as its main means of delivery. As such, the game generated are evaluated and considered as the final output of this kind of work.

While game work type focuses on the entire object of a game and views the PCG content generated as an output, generator work type focuses more into a single aspect being generated in the game and measures the content generated instead of the entire game itself being evaluated.

Based on figure 4, a vast majority of the papers analyzed focuses on generator work type which is not a surprise as generating a single aspect inside a game by using PCG is far easier compared to generating a game by using PCG as its main means of delivery, while at the same time also shows a more advanced work being done compared only to preliminary ideas. As such, implementation and development of contents as a proof-of-concept and evaluating them in a testbed is particularly important on works that focuses on PCG, while it is not entirely necessary to do such for novel and newer preliminary ideas which require further testing.

Form of analysis work type being done is more of an exploratory analysis of a particular method [27], inferring external aspects based on works being done by using PCG [28]–[30] which mostly focuses on socio-cultural aspect in term of existing game usage, or creating an analysis of methodology of currently existing method of PCG [31]. Another form of analysis work type based on paper analyzed is on argumentation of an existing method of PCG along with its reinforced ideas.

A small number of papers which focuses on framework mostly focuses on improving existing ideas with models to increase its legitimacy and novelty, such works may also count as a preliminary work as the work being done are not being tested yet but the argumentation and theory along with a model has been proposed to tackle a particular problem, usually it is with attached future works for further development phase. Such framework work type may include diagrams [32], system architecture [33], or intricate algorithm and basic design phase [34], [35]. However, some frameworks might be tested as it is a generator by using fitness evaluation and analysis [36], thus it is not entirely possible to categorize one work type into an independent or strict category based on its work type.

Addressing the majority of paper found, generator is the most common type of PCG implementation. Based on the paper found, majority of the papers that focuses on content generation is either fully generating contents for the sake of the PCG, or using PCG as an applicative means to create content for games – be it an existing games or new game entirely.

2. Focused Content

This part of the result sub-chapter answers RQ6: What content being focused are being researched based on the existing researches?

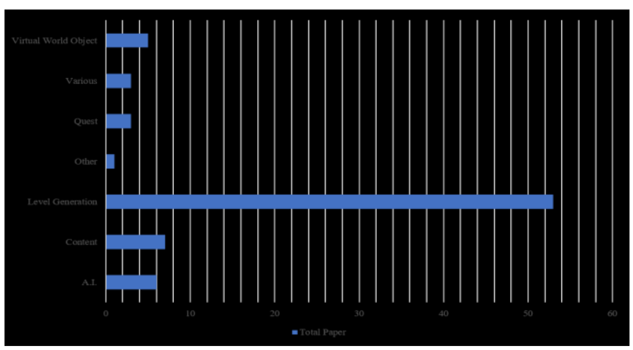

Figure 5. Total number of papers based on its focused content.

PCG focused contents are defined as the contents which PCG approach is being adapted. In this context, PCG are being adapted into contents whether it is into a form of game, or when the work is not creating a game as a testbed. Based on the figure 5, a vast majority of the research are focused on level generation, which is not a surprise considering PCG are most suitable to create variations of playable level inside a game, apart of that, general content and artificial intelligence are also an emerging content being focused in the current state of researches. Several minor contents such as quest generation, virtual world objects, as well as other type of contents are also included in this manner.

Focusing more on the level generation focused contents, multiple works are done to either create the contents by using PCG [27], [37], [46], [38]–[45], thus automating the content generation in the game in term of its physical contents. While several other works improve such content generation into the logical contents of the game by focusing into its game difficulty [47]–[56], creating an adaptive and adjustable level generation personalized to each unique user.

Multiple level generation focused contents tend to alter the map creation process in form of either a platform where the player plays the game such as mazes [57], [58], cave systems [59], or tracks of traversable areas [50], [60], [61]. Another result also shows map generation focused on games that involve procedurally generated dungeon mechanism [62]–[64] which makes an elaborate level multi-level playable area based on a particular game genre/mechanics.

In term of A.I., PCG are used intensively to create an adaptable A.I. that would adapt its behavior based on user decision, hence creating a dynamic environment similar to the level generation, but instead is adapted to the opposing player in the game instead of altering the playable area [65], this adaptation of PCG into A.I. are also adapted into a more extensive A.I. that even can create its own game [66], [67], such as related to previous sub-chapter of work type where the generator generates an entire game instead of contents inside a game. The adaptation of PCG into A.I. are mostly targeted to learn the player pattern and create challenge to the player based on its unique activity, creating a different playing experience for each players [16], [68], as well as using multiple player activity to evolve the A.I. to be able to do more meaningful decision [69]. A more general content being generated by using PCG is categorized as "content" on the figure as it does not focus on a single content but rather creating an entire system of its own as an output [70]. In term of quest focused content, several form of PCG has been known to be able to create a set of narration and stories [71], [72], while other contents are more niche such as generating music [73] or instructions for players [74].

3. Method, algorithm, and approaches

This part of the result sub-chapter answers RQ7: What kind of method, algorithm, and approaches are being researched based on the existing researches?

There exist numerous types of method, algorithm, and approaches in PCG, such that multiple researches based on paper found are very varied and is hard to categorize them into a certain category, as such, the result is then listed down based on what type of approach that is most common and popular among the paper, Table 3 below shows the list of methods, algorithms, and approaches, listed down alphabetically and elaborate briefly on its usage based on the existing research context.

Table 3. Papers based on its method, algorithm, and approaches.

Method/ Algorithm/ Approach Name	Source	Explanation
Answer Set Programming (ASPP	[75], [42]	Answer set programming (ASP) is one of the existing programming approaches that can be used to deliver PCG contents, it is a specific programming approach that is used for solving combinatorial search problem, such that involves a search tree based on known facts related to the problem and rules. Such method has been

Method/ Algorithm/ Approach Name	Source	Explanation
		observed to be able to create contents such as a dungeon level generation [75]. Another research also has been done by combining ASP with evolutionary algorithm to generate and optimize maps in a level generation by utilizing ASP logical nature [42].
Artificial neural network (ANN)	[76]	Artificial neural network (ANN) is a form of computing system that is designed to mimic how the human brain works, instead of calling it a model or an algorithm, it works more like a framework due to its nature of applying multiple machine learning algorithm on its process, nevertheless, on this context, ANN is considered to be a method of delivery to create a PCG outputs. As a framework, the work is usually done by combining the said framework with multiple other algorithm, one work combines Big-Five model, nondeterministic planning algorithm, along with ANN to create a personalized interactive storytelling, by using the player behavior to generate player-specific quests [76].
Coevolutionary genetic algorithm (CGA)	[16]	Coevolutionary genetic algorithm (CGA) is an advanced form of evolutionary algorithm that utilize a subjective fitness value, such that the evaluation of the individuals in the algorithm are evaluated based on its interaction with other individuals. CGA usage in delivering PCG are more focused on decomposing complex design problem by using such algorithm to generate a solution while avoiding early convergence state, thus creating a more optimal result. Creation of A.I. in game by using CGA has been proven to be optimal [16], creating a more challenging and fun game to play with.
Dynamic Difficulty Adjustment (DDA)	[48], [49], [77], [78]	Dynamic Difficulty Adjustment (DDA) is a popular form of PCG deliverance method due to its simple mechanism, more focusing on creation of logical aspect of the generated content in form of game difficulty, DDA has been seen to be used in multiple researches over the years. DDA mechanism works by using player's ability in the game and use it as the input to adjust the game difficulty dynamically, targeted to create an engaging game experience that is neither boring or too difficult for the player. One of the works that has been done focuses on using DDA by combining it with Big-Five model to create a level with various difficulty based on player enjoyment and duration [49]. DDA is also used to balance the game by punishing player by spawning obstacles based on player's tendency to abuse a certain game mechanic [48]. DDA has also been proven to be useful on rehabilitation games where therapy session difficulty is adapted by player's current achievement on finishing a task in the rehabilitation [77], such that the difficulty does not always goes up incrementally, but instead adapts to the

Method/ Algorithm/ Approach Name	Source	Explanation
		player physical condition and result of previous therapy. A combination of DDA with indirect biofeedback (IDF) has also been done to create an immersive procedural horror games by using player's biological and emotional reaction to generate events in the game [78]. DDA adaptability is thanks to its simple mechanism of adapting a certain type of method and easy adaptation with other algorithm or models to deliver PCG.
Experience-driven procedural content generation (EDPCG)	[33], [69], [79]	Experience-driven procedural content generation (EDPCG) is a more generic PCG which uses player experience to generate a content, rather than specifying it like DDA or evolving a solution like CGA. As such, any input that is experienced by the player such as basic gameplay experience [69], activity and skills [79], or even an external data such as after-game questionnaire [33] can be considered to be a EDPCG. Due to its generic choices, EDPCG is rather too flexible if not defined or focused into a more specific approach, but its usage has been proven to base other existing methods.
Genetic algorithm (GA)	[52], [80]	Genetic algorithm (GA) is a more general form of CGA which uses the concept of natural selection and rules to generate solution based on given population (called chromosome) and changing its value by using mutation and crossover, in PCG creation, rather than using the player action as an input like DDA and EDPCG, GA uses existing level as a base to generate more level with similar difficulty or similar content [52]. While it is also not impossible to use player input as a form of chromosome for GA selection process, a research has been done in this form of GA implementation in an educational game [80] to generate questions by using PCG by using GA approach.
Human-in-the-loop	[51]	Human-in-the-loop approach is a form of PCG creation method that uses human input to interfere the result and adjust the result rather than using algorithm to fully do the generation process. This might sound counterproductive, but it has been proven to be able to create a much more refined result by increasing the aesthetics and difficulty of the PCG output. Due to the rigid nature of algorithms, the aesthetics of the level generated by an algorithm looks less appealing albeit having a considerable level of difficulty, human-in-the-loop approach improves such problem by doing a minimal adjustment to create a visually pleasing output [51].
Monte-Carlo tree search (MCTS)	[81], [82]	Monte-Carlo tree search (MCTS) is an algorithm consisting of selection, expansion, simulation, and backpropagation used in a combinatorial problem for games with multiple viable solution that changes every with every action done such as chess. Due to its stochastic nature, MCTS are able to measure play patterns and create a design space based on the patterns

Method/ Algorithm/ Approach Name	Source	Explanation
		[81]. MCTS also has been applied on rehabilitative games to create a game quest as well [82].
Search-based procedural content generation (SBPCG)	[40], [60], [83], [84]	Search-based procedural content generation (SBPCG) is the counterpart of EDPCG which focuses on the searching aspect of PCG rather than using the experience as the driving factor to create a PCG. As such, it is a very general type of PCG which usually combined with multiple algorithm albeit not necessary. SBPCG has been done to generate levels [40] and maps [60], [83], [84], but often are more geared towards a pilot study due to its nature of searching instead of using player experience as the major decision choice.

4. Game models and game genre

This part of the result sub-chapter answers RQ8: What game models are being implemented with PCG based on the existing researches that focuses on serious games? And RQ9: What game genre are being implemented with PCG based on the existing researches that focuses on serious games?

Table 4. Total number of papers based on its game model.

Game Model	Total Papers
Story-Based	2
Real-time Strategy	2
Racing	2
Platforming	19
First Person Shooter	7
Fantasy	3
Card-Based/ Board-Based	5
Others	6

Game models are defined as generic models that are based on its core mechanism, while game genre are generic composition and generalization of such models. For instances, a platformer games are any games that utilizes a platform that can be used by the player to move or to do any action, if such game requires the player to move and do actions in real-time, the game is categorized as action games. There exist however several papers that does not mention its game model nor its genre, as such, it is inferred based on the output of the paper for the sake of convenience. Table 4 shows the distribution of papers based on its game model. Additionally, the result is then listed down in a form of table in Table 5 which shows a further explanation of the results.

Table 5. Papers based on its game model.

Game Model	Source	Explanation
Platforming Games	[52], [85], [86],	Based on the result, majority of the papers researched are focused on platforming games, the usage of PCG on the papers found are focused on several key contents of the

Game Model	Source	Explanation
	[87], [88], [89], [90], [91]	game such as world generation [85] and level generation [86], [87], and is used for multiple reason such as creating variations and aesthetics [88], reducing workload by using PCG [89], generating variations and automation of in-game mechanics [90] or purely for experimental setup by using existing game as an example [91]. Platformer game utilizes a platform as a playing field for the player to do its actions, due to its nature, PCG are able to alter the playing field by using multiple methods [52].
First Person Shooter	[92], [93]	Another prevalent game model that uses maps are first person shooter (FPS) games, where a player controls an in-game avatar that has a first-person view as if the player is seeing the object in real life. Similar to platformer games, maps can also be generated using PCG [92]. Not limited to maps, FPS require players to face another player as an opponent, be it another human player, or an A.I., which in fact, can be generated procedurally by using PCG [93].
Real-time Strategy	[17], [83], [94]	Real-time strategy (RTS) games are strategy games that require players to do their action in real-time manner, but does not require such finesse of movement precision but more of a chess-like actions. Similar to FPS and platformer, it also has a playing field that can be generated using PCG, the generated playing field are by no means perfect, as such, the aesthetics level of generated content may not be the same as hand-made ones, but the generation of such content may outweighs the aesthetic penalty [15]. Similar to RTS card and board games can also be implemented with PCG concepts to generate its content such as board layout [17], [83], [94].
Story-Based Games; Fantasy Games	[95], [96], [97]	Story-based games and fantasy games utilizes PCG in a different manner compared to previous models mentioned, focusing on creating a dynamic story contents by using PCG as a means of generation [95]–[97].
Sandbox Games; Sci-fi Games; Management Games	[98], [99], [100]	Other lesser game models utilize PCG for its content generation similarly, such as sci-fi to generate levels [98], sandbox games to generate player's appearance [99], as well as dialog generation for management games [100].

Based on its game genre, as shown in Table 6, action games are more favored due to action games usually plays in a level or playing field, as such, most action games are also a platformer games [38], [48], [52], [93]. Sandbox simulation games as mentioned earlier also taken an advantage by using PCG to generate player avatar as sandbox simulation games able to create countless amount variations [99]. As well as story-based simulation games to generate its dialog and story by using PCG [39].

Table 6. Total number of papers based on its game genre.

Game Genre	Total Papers
Action Games	27
Puzzle Games	4

Game Genre	Total Papers
Racing Games	2
Role-Playing Games	4
Simulation Games	4
Strategy Games	7

4 Discussion

4.1. Research gap

Based on the result stated previously, there exist several research gaps that can be inferred from aforementioned results. In this paper, research gaps are derived from the inference of specific set of papers from the research questions. Such inference is done based on similarity of topics being researched either from the domain researched or the type of PCG being done.

On a specific domain of serious games, papers with clear game-related contents are more focused on generating contents inside the game instead of using PCG as the main method of creating the game, with a little amount of paper using PCG as a testbed to prove their results [65], [87], [93]. With most paper focusing on level generation among all types of content generation, a gap can be inferred that more niche usage of PCG for contents that are not level generation are still uncommon, albeit it is understandable why PCG on level generation is to be expected. Another gap is shown on the application of PCG based on its game genre and game model, action game genre and platforming game model are more prevalent compared to other game models and genres.

More on the focused content, as mentioned before, level generation are the most prevalent type of content being focused on PCG researches based on paper found, however, several other contents such as quests [76] and world objects [85], [96] also exist to a certain extent, as such, any form of non-level generation PCG would have a rather large novelty compared to level generation.

4.2. Empirical Evidence

Empirical evidence on this research are defined as a proof based on findings of the current result, solidifying the idea of how trends over the past few years research of PCG are being done and how such trend would show the future of PCG in game-related contents.

Over the past 5 years, based on the paper found there are no clear trends on what method or algorithm that are popular during specific years, signifying the that the concept of PCG are still evolving, multiple methods are tested on multiple types of contents, effectiveness and efficiency are being tested as well as the aesthetics of the content being generated, PCG contents are targeted to be seamless and seems natural, even though such results has not been achieved fully yet. Adaptiveness and dynamics of the content being generated is also highly debated as PCG are meant to be one of the means of reducing human workload in generating contents. Based on this result, PCG is a valid field of research in game-related contents, be it in form of games itself, or game-related contents.

Another inferred evidence can also be derived that PCG are mostly used to reduce human workload in multiple aspects, such as time, efficiency, automating processes, generating quality content without using human input, or even creating something beyond human capability. PCG are also used to alleviate the human limitation as machine has no energy limitation.

5 Conclusion and Recommendation

5.1. Conclusion

This paper presented a brief literature review in the area of PCG in games over the 5 years period. There exist 78 papers being researched on this study. This paper focused on basic overview of the paper identity such as source, years, paper type, and research level, as well as PCG domain of work type, focused content, as well as the algorithm or method being used. This paper also mentioned briefly about game genre and game model in respect of how PCG are being used on such genre or model respectively.

Majority of the paper found are on the last 3 years signifies the emerging field of PCG as a field of study with prominent amount of research done in form of conference proceeding which represents a growing interest of the field as well. With most paper focusing on generator work type and level generation form of focused content, PCG has shown a clear usage, although there exist multiple work type and focused content as well.

5.2. Recommendation

This study provided a brief empirical evidence on how PCG are being used in game-related content for researchers. However, due to limitations and constrains, some following future research directions may became evident. The limitation of time constraint that is used on this study may lead to a research with either broader timeframe or newer papers. The limitation of category in the result section can be used to create a new category of information that can be elicited and used for a direction towards a new more sophisticated and specific paper.

A further analysis on how PCG are being evaluated and quantified in a better classification, the existence of multiple methods, algorithms, and approaches shows a direction that may be directed towards a literature review that solely focuses on the classification of such methods, algorithms, and approaches. Another direction that can be done is to direct the research to a more specific emerging field of educational games and game-based learning in which the implementation of PCG in an educational context might proof to be an interesting approach. Due to the lack of further explanation of elaboration on quality characteristic of the game where PCG are being used, another specific direction can be taken to focus on the game aspect to how PCG affects several game models or game genres.

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