# Game Abstraction (GA) Using Temporal Event Similarity With Uncertainty

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#### Abstract

While describing a game, details of game moves in a commentary are not considered, which loses the data. Due to lack of expertise in writing or narrating the game, surprises cannot be revealed completely which loses the interest of game abstract description. The actual spectator has more information about surprises, gameplay, and game conditions in his/her observation of the game. The surprise-based abstraction of the game represents more information than other descriptions. The writer's perspective, reader's perspective, and viewer's perspectives are different which has more information; each one having its perspective for the game surprises. The unrevealed surprises can be mined from each perspective which might create interest in the description. Existing statistical models do not cover these perspectives and surprises. An abstraction of these multi-perspective surprises is proposed in this paper. The surprises are calculated with the help of event uncertainty in the game. The surprising similarity can be measured for various games which can help to decide the game plan, strategy, player style, team psychology. The surprising similarity can be measured with the help of uncertain events in times series of surprises. The surprise-based similarity is compared with the time series similarity measures. The surprise-based similarity game comparison has improved. The surprises can also be revealed in other time-series data like stock market data, network traffic data, etc.

Keywords: Game Abstraction, Uncertainty, Surprise, Time Series

### **1** Introduction

In the current era of multimedia and computing, more and more games are played. They are designed, strategized in such a way that people especially the gaming community should get attracted as well as the new generation too. In recent development, most games are getting attention based on internet advancements like online gaming, multiplayer gaming, and social gaming. These types of new gameplay approaches are evolved and got accepted by gaming communities open-heartedly in computer games.

If anyone can observe computer game development, it has a direct co-relationship with computational evolve. Earlier games are dos games and having less computing related to graphics. As gaming improved in graphics and designing part more complex games were developed which has the computer as an opponent. As computer movements are strategically fixed one having less uncertainty, these games lose interest in gaming communities regardless of their visual effects. Hence, there is a need fora person to person or human to human gameplay and multimedia games are evolved, which got the support of the internet revolution to get more and more interest in online multiplayer gaming. In the recent era, online gaming is most famous and played daily by the young generation.

Gaming strategies are also used in different business development under a computational domain called Gamification. These strategies are incorporated in business for various applications like promotional strategies, social media, engagement, etc. All these strategies make an impact differently based on domain and utilities. In the case of gaming considering brand loyalty if the offer is given such strategies can be adapted in businesses. Some strategies are used to sustain in the market, in such cases new updates or free features are provided for the product to add interest in the product. Like feature phone came with music as utility added which attracted many customers. Hence to stay in the market other feature phone producing companies were also adding these features.

As discussed, there are various ways to apply gaming strategies, but these strategies can be only compared if moves are compared in between them. Most of the time while watching football, or cricket game, anyone can relate special series of moves which can be referred to as event is similar to another match event like Rohit Sharma hit six to Hussain Ali in world cup 2019 is exactly similar to Sachin Tendulkar's six to Shoaib Akhtar. Here, Sachin Tendulkar didn't hit uppercut once only neither Rohit Sharma but why only these two shots are considered similar? The reason is simple these two events are having many similarities and other uppercut didn't. Human nature tries to measure maximum similarities in an event to say both are similar or not. Here similarities are on the different levels like cricket World Cup event, against Pakistan, against one of best bowler of that era, top player, opener, the direction of bowl hit, wide short pitch delivery, etc. Such all similarities are measured in the sequence of events lead to result in these two shots are similar.

Human nature also always tries to find uniqueness in events to say similarities, many cover drives are played in the world cup which is not compared for similarities but events having moves like straight  $\rightarrow$  cover  $\rightarrow$  pull such sequence comes then analyst rate it for similarities. Hence uniqueness in game-play and sequence matters to find out similarities. This is observed in the same way because other statistical data do not provide actual play similarities in matches. Hence sequences needed to be mapped for similarity measures. In this paper, uncertainty-based unique events identification and their association to find abstract event similarities in a sequence of events are computed to find similarities in the player, player style, and match similarities.

#### 2 Literature Survey

The main stage of discovery of knowledge discovery from time-series data requires sequence analysis. The input sequence could be modelized as time series sequences even they are text or multimedia inputs. In general, numeric data provided in sequence of series for medical and other domains like moves in case of games or sports can be modeled in sequence input with time associated i.e. time series inputs. Many researchers used an integrated approach to discover the knowledge. For this, collaborative and distributed approaches to computing are used [1-3]. Some of the researcher used social media dataset [4], review dataset [5], pre-knowledge of Wikipedia to extract useful information [6-8].

These sequences are compared and analyzed in a different way to derive different inferences by just comparison. Based on information gain in world sequencing and uncertainty associated, sequence comparison is performed by Vigna et al. which represents Euclidian distance between the sequences. They provide results in different formats angle between words and information, covariance, correlation, information theory, Kolmogorov measures, and Universal sequence map [9]. Different alignment and algorithmic techniques are given for subsequence comparison which leads to knowledge discovery in the form of different patterns [10]. Similarly, biological sub-sequences are compared for pattern determination using AI computational methods [11-14].

Once sequences are analyzed and compared, based on inferences, these are modeled in different knowledge models. F. M<sup>o</sup>orchen et al. created a framework that finds the muscle active information extraction mechanism. They extracted time-series data acquired from kinesiological EMG to find the pattern for multivariant input sequences [15-17]. To build knowledge there is a necessity of evidence of activities and their documentation in the physical system. Here activities could be drop-down to events for time series input sequences. The cases are mapped to each event to build knowledge in various forms, it may be relationships, graphs, or any other mathematical representation available [18, 19].

Sequences are categorized in events by some researchers to analyze it in case of time series analysis. LeadLine is one of event identification interactive visual analytical situations, which integrate topic modeling, event detection (identification) and name data entity relationship based on 4W's (Who, What, When, Where). The knowledge is mined using time sequence referencing and visually represented to extract more knowledge for decision making. Then they are represented as entity graphs and geo-mapping based on the position of the context in the text [20]. A mathematical representation of event detection for time-series inputs is given by Kom [21]. Similarly, in a nuclear powerplant, to find abnormal event neural network is used [22]. Also, for medical domain event discovery from time-series data [23] EEG signals are processed to find an event for knowledge discovery [24]. In the domain for the social network, based on the post-event is tried to determined using text or other multimedia inputs [25-27]. For finance, sector events are determined based on transaction, notification, and news as inputs [28]. There are various approaches discussed to identify the event from the different domains for knowledge discovery which will help in decision making [29, 30].

These events are clustered and classified for decision-making. By applying fuzzy cmeans on the knowledge extracted by using time series frameworks and sub sequencing using Hidden Markov Model to improve the predictive power [31]. Different clustering approaches are applied for time series subsequences inputs [32-35]. Similarly, Deep Neural Network is applied for different Supervised learning approaches i.e. for classification [36, 37]. Table 1 shows the literature review.

ID	Author	Findings	
12			
[1].	Gurparkash Singh,	<ul> <li>Collaborative</li> </ul>	
	Louise Hawkins, and	Knowledge Building	
	Greg Whymark	(CKB) based on	
		cultural-historical	
		activity theory	
[2].	SannaPekkola, Petri	• Knowledge maturity	
	Niemi & Juhani Ukko	model: OSSIC review	
[3].	Jim Hewitt and Marlene	Computer-Supported	
	Scardamalia	Intentional Learning	
		Environments	

Table	1:Literature	Survey
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		(CSILE)
[4].	Jun Oshima.	• Knowledge Building
L 1.	RitsukoOshima,	Discourse Explorer
	Yoshiaki Matsuzawa	(KBDeX).
[5].	Deborah Finfgeld-	• Content analysis and
	Connett	synthesis
		• Quantified review of
		knowledge building
[6].	Ulrike Cress & Joachim	• CKB on wiki
	Kimmerle	knowledge using
[7].	J. Moskaliuk, J.	equilibrium activities
	Kimmerle& U. Cress	
[8].	Joachim Kimmerle,	• Three technologies
	Ulrike Cress, and	introduced using the
	Christoph Held	wiki, Social tagging,
		pattern-based and
		use of wiki
[9].	Susana Vinga and	• Information theory-
	Jonas Almeida	based, word
		sequence-based,
		word angle based,
		and word distance-
		based sequence
[10]		mapping
[10].	Tak-Chung Fu	• Whole sequence
		• Subsequence
[11]	Kun Maa Chaa Laurin	matching
[11].	Zhang	• Different alignment
	Zhang	• Different
		• Different algorithms
		comparison
[12]	William R Pearson	• Comparison between
[+4].		algorithm FASTP and
		FASTA

	David J. Lipman	compare biological
		protein sequences:
		FASTA, RDF2,
		LFASTA
[14].	Michael Levitt, and	• Comparison between
	Mark Gerstein	FASTA and BLAST
		Sequence comparison
		algorithms
[15].	Guy St C Slater and	• Sequence comparison
	Ewan Birney	using heuristic
		bounded sparse
		programming
[16].	Fabian M¨orchena,	• TSKM Framework
	Alfred Ultscha and Olaf	• Primitive pattern
	Hoosb	finding
[17].	Fabian Mörchen&	• Time series
	Alfred Ultsch	knowledge
[18].	Fabian Moerchen	representation (TSKR)
		• Fast interval pattern
		finding using depth-
		first and marginal
		pattern approach
[19].	Donald Philip	• Teaching Knowledge
[20].	William Cerbin and	building framework
	Bryan Kopp	
[21].	Wenwen Dou, Xiaoyu	• Event identification
	Wang, Drew Skau,	using LeadLine and
	William Ribarsky, and	4Ws
	Michelle X. Zhou	
[22].	Edward L. Kom, Barry I.	<ul> <li>Mathematical</li> </ul>
	Graubard, and Douglas	analysis to identify
	Midthune	task from time series
[23].	YukiharuOhga and	• Neural Network-
	Hiroshi Seki	based abnormal
		event identification
[24].	Christine L. Tsien	• Medical event

		discovery using
		medical time series
		data analysis
[25].	Vernon Lawhern, W.	• Artifact detection in
	David Hairston, Kay	EEG based on event
	Robbins	identified and classify
[26].	M´ario Cordeiro(B) and	• Event detection and
	Jo~ao Gama	discovery: RED, NED
		• Supervised and
		unsupervised event
		detection
[27].	Anuradha Goswami,	• Social text stream
	Ajey Kumar	based event detection
		<ul> <li>Detailed survey</li> </ul>
[28].	Farzindar Atefeh And	• Different event
	Wael Khreich	detection for Twitter
		text dataset
[29].	Richard E. A. Escher	• Neural network-
		based financial event
		detection
[30].	H. Langer, S.	• Five fundamental
	Falsaperla, T. Powell, G.	classes: Volcano-
	Thompson	Tectonic Events,
		Regional Events,
		Long-Period Events,
		Hybrid Events, and
		Rockfalls.
		Identification and
		classification of these
		transients, which
		have been hitherto
		carried out manually
[31].	SoheilaMehrmolaei and	• Statistical and ARIMA
	Mohammad Reza	based classification
	Keyvanpourr	for events
[32].	Vasile Georgescu	• Performed Time-
		series clustering

		especially fuzzy c-	
		means clustering	
		• Improvement in	
		predictive power	
		using HMM	
[33].	Saeed Aghabozorgi, Ali	• Different time series	
	SeyedShirkhorshidi,	clustering	
	The Ying Wah	approaches:	
		wholistic, time	
		subsequence, time	
		point clustering	
[34].	T. Warren Liao	• Different clustering of	
[35].	Geeta Shikka	time series survey	
[36].	Sylvia Frühwirth-	• Markov Chain,	
	Schnatter	Bayesian, and Monto	
		Carlo approach for	
		clustering	
[37].	Hassan Ismail Fawaz ·	• Time Series	
	Germain Forestier, ·	Classification (TSC)	
	Jonathan Weber, ·	•Use of CNN-based	
	LhassaneIdoumghar, ·	deep learning.	
	Pierre-Alain Muller		
[38].	Eamonn Keogh, Shruti	• Use of classification,	
	Kasetty	clustering, indexing,	
		and segmentation for	
		the importance of	
		time-series data	

#### 3 Proposed Game Abstraction (GA) System

In the case of similarity measurement, statistically, similarity only provides results of move, the sequence of moves, or match results. Ex Australia Vs South Africa cricket match held in 2006 at Johannesburg can be mapped both innings are similar on key events that happened in a match like the run rate at 10 or 20 overs but the match is different with opening partnership and in other constraints. These small changes are not articulated when events are mapped statistically. Here uncertainty in the form of surprises played a very important role. Sequences are needed to be mapped along with statistics in events. Hence, the system is proposed based on uncertainty available in sequences as well as uncertainty in statistics. Figure 1 represents an uncertainty-based abstraction of game events. In the proposed system sequences uncertainty is computed with statistical uncertainty is computed. These with event similarities are used to determine similarities for different similarities.Context-Li [39] Model is used to limit uncertainty which is out of bound. Like in cricket beamer ball batsman doesn't need to play the delivery hence uncertainty related to this can be omitted while operating.

Cricket commentary is used as game inputs. For text commentary bag of words, the approach is applied to find surprises in the text, and features are extracted, represented in *FM* matrix with weights in *WM*matrix as shown in figure 2. Events from the game filtered for surprises and relevant abstract events are filtered. Like in cricket; single and double run doesn't provide as a surprise as six or four runs. Then, Surprise Index(*SI*) in the domain of [0,1] is calculated on filtered data as a function based on *FM* and *WM*as:

 $SI = \{BoW, n - gram, Wordnet\}$ (1)

#### Figure 1: A Game Abstraction System using Surprises

Based on *SI*calculated for each commentary used abstraction. Usually, human tries to an abstract situation based on his/ her perspective. Here without considering such biased perspective abstraction is provided for Cricket commentary. It improves accuracy while considering surprises in events while abstracting.

#### 4 Results and Discussion

IPL Cricket commentary is used from cricbuzzAPI. The dataset is created has **54\*240** (one season data with each delivery commentary of 54 matches and each match has 240 deliveries)

Over	Commentary	SI
	Nehra to Mandeep, FOUR, first boundary for Mandeep	
	and RCB. Full and on the pads, needed to be put away	
	and Mandeep did just that, picked it up and dispatched it	
0.5	over mid-wicket, couple of bounces and into the fence	0.33
	Nehra to Mandeep, FOUR, back-to-back boundaries to	
	end the first over. Again, Nehra is a tad short in his	
1	length, Mandeep had the width to cut and he didn't try to	0.18

**Table2: A Sample Commentary and SI** 



#### Abstraction Sequence Clustering comparison

Dataset is filtered and *SI* is calculated. Table 2 represents from commentary based on *SI* matches events are represented. It is seen that *SI* is different but statistics is four runs and can have more meaning in abstraction. Figure 3 represents sequence clustering results of all events. Based on *SI* and statistical data as shown in table 2 sequence clustering was performed to measure abstract level similarity. The results improved due to surprises in the match is considered, by clustering in abstract level two players or two matches are similar or not.

#### **5** Conclusion

Automatic abstraction or summarization misses important events or it is biased with the person. This reduces the visibility of news or another document. It happens more with fast dynamic events like gaming etc. where there are each event is unique. Finding out the most suitable event in summary or abstract is mostly computed manually. Using surprises from inputs, abstraction might provide more meaning. Adding uncertainty based computation again filter and refine surprises. Here significant improvement for similarity measurement as well as in abreaction will help in multiple domain applications like share market, online transaction, etc.

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