Turning Wisdom and Effort of Crowds into Complex Video Annotation

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ABSTRACT

This paper presents a general approach to perform crowdsourcing video annotation without requiring trained workers nor experts. It consists of dividing complex annotation tasks into simple and small microtasks and cascading them to generate a final result. Moreover, this approach allows using simple annotation tools rather than complex and expensive annotation systems. Also, it tends to avoid activities that may be tedious and time-consuming for workers. The cascade microtasks strategy is included in a workflow of three steps: Preparation, Annotation, and Presentation. A crowdsourcing video annotation process in which four different microtasks were cascaded was developed to evaluate the proposed approach. In the process, extra content such as images, text, hyperlinks and other elements are applied in the video enrichment. To support the experiment was developed a toolkit that includes Web-based annotation tools and aggregation methods, besides a presentation system for the annotated videos. This toolkit is open source and can be downloaded and used to replicate this experiment, as so to construct different crowdsourcing video annotation systems.

CCS CONCEPTS

• **Information systems → Multimedia information systems**; **Crowdsourcing**; • **Human-centered computing → Web-based interaction**; **Computer supported cooperative work**; • **Applied computing → Annotation**;

KEYWORDS

Crowdsourcing, Video Annotation, Human Computation, Microtasks, Multimedia Systems, Video Enrichment

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1 INTRODUCTION

Video is a very effective information container, and it is a highly expressive type of media, capable of providing a large semantic load by presenting different audiovisual components coherently[27]. However, video can be considerably more useful when carrying metadata that can be used by video applications and is often represented as video annotations.

Video annotation involves inserting tags into video objects to describe their content and context, also to describing media characteristics such as quality, coding, among other features [38]. It allows highlighting key points as well as add information to content presented[8]. In other words, they are used to make easier the work of users and systems that can handle annotated items.

These annotations facilitate the creation of video applications for content-based distribution [41], indexing [42], summarization [13], navigation [17], composition [39], among many others, by both automatic and manual means [37].

In this paper, video annotations are categorized as simple and complex ones, considering that simple annotations are those that can be acquired with a simple interaction of the workers in a microtask. Complementarily, a complex annotation is one that requires the worker execute a more tedious, hard or time-consuming task, in which he needs to perform multiple interactions.

For example, football (soccer) videos can be annotated to identify relevant events in the game, such as goals, cards, and fouls [32]. In this paper, this is considered a simple annotation activity because requires a single annotation task to capture one of these events and the instant when it happened. A system that is able to process these annotations can use them to generate summary versions with the match's most important moments, to provide markers for positioning the video in each event, among other applications.

However, this example can be improved with additional annotations such as which player scores a goal or receives a card. The complexity can still increase by including annotations about how the goal was or why a player received a card. As video annotations become more complex, the annotation tools need to be more elaborate, also annotation tasks are more costly.

Automatic methods for video annotations often present satisfactory efficiency and interesting results, though, these methods generally apply techniques that require well-structured videos and extensive examples database, such as deep learning[24]. Unfortunately, many scenarios cannot provide these requirements, making it impossible to use automatic methods for video annotation [26].

In another way, manual video annotation is suitable for these scenarios because it uses human intelligence to handle the tasks. However, manual video annotation can be high-costly because of the potentially high-density of annotation points in the video, as well as the complex nature of some annotation tasks.

An alternative to achieving a video annotation in a general scenario is to employ collaborative or cooperative approaches, which are differentiated in this paper. In a collaborative approach, the contributors work together to solve the main problem. Otherwise,

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in a cooperative approach, each contributor solves a part of the main problem to produce a final result [25].

Taking cooperative approaches to a higher level, crowdsourcing video annotation has emerged as a proposal to annotate videos using a large number of contributors efficiently [35]. Following the crowdsourcing principles, the tasks distributed to the workers are modeled to be done independently, maximizing the parallelism [20]. Moreover, each task can be sent to many contributors, making possible to compare, check and to aggregate the contributions also reducing the chance of producing a biased result [16].

A frequent problem of using a crowdsourcing approach to video annotation is to balance the relationship between task complexity and cost. Simple annotation tasks, such as clicking an object on a video, can be done in a few seconds for anyone. Otherwise, more complex tasks such as providing complementary content and positioning it in the right position on a video, require some expertise of contributors and are more costly to them. In a crowdsourcing context, microtask is a ubiquitous designation for simple tasks that can be performed for any contributor quick and easily [12].

Into this scenario, the approach introduced aims to provide ways to get around some issues faced in achieving video annotation.

- By using manual annotations, no example bases or restricted conditions are required as in automatic methods.
- By using a microtask-based crowdsourcing process is not required experts nor trained workers. Also, it makes the contribution process simple and quick, avoiding time-consuming and tedious tasks to workers.
- By using microtasks in which only a simple annotation is collected is not required sophisticated annotation tools.

The rest of this paper is structured as follows. Section 2 presents related works. Section 3 presents the approach introduced by this paper. Section 4 presents the conducted experiment. Finally, section 5 concludes the paper presenting final considerations and future prospects.

2 APPLIED CONCEPTS

2.1 Video Annotation

– Simple vs Complex

2.2 Human Computation

– Modeling Taks

2.3 Human in the Loop

– Annotation Tools

2.4 Crowdsourcing

– Cooperation vs Collaboration – Microtasks vs Macrotasks

2.5 The Wisdom of Crowds

– Crowd vs Experts – Aggregation Methods

3 USED TECHNOLOGIES

3.1 Web Systems

– Video Streaming – Web Multimedia Players

3.2 Digital TV

– NCL

4 RELATED WORK

Crowdsourcing video annotation approaches are used in various applications and are used to gather information of various types, such as temporal synchronization[9, 40], events[23, 34], scene objects[1, 29], emotions[5, 31], actions[10, 30], quality[14, 19], geo-tagging[7, 18], social relevance[4, 21, 33] and captions[11, 22].

However, some of these works are based on complex annotation tools, demanding hard, tedious or time-consuming tasks, or requiring trained and skilled workers. Some relevant examples that should be regarded include works such as [1, 5, 10, 18, 21, 28, 36].

VidWiki[1] is a complex system to improve video lesson by video annotation, which provides a complex annotation tool(Figure 1) that allows the worker to edit video scenes by adding various types of annotations, including LaTex equations. Another interesting paper to note was written in 2012 by C.Vandrick[36], in which time-consuming complex tasks were deployed in the Amazon Mechanical Turk[18] demanding specialized work to perform them.

While these works often produce interesting results, to adopt complex annotation tools, as well as hard and time-consuming tasks, restrict potential workers and owners capable of developing complex tools and hiring skilled workers.

Figure 1: VidWiki annotation tool[1]

There are also papers on crowdsourcing video annotation that report the use of simple tools and microtasks that can be done quickly by unskilled workers. These works include [6, 9, 15, 23, 29, 30, 34, 40].

The work published by N.Gagil in 2014[15] uses a very simple annotation tool(Figure 2) that allows the workers to perform an easy microtask, which consists of annotating videos with surveillance problems if any of them are found.

ReTool[6] is a work that must be mentioned because it presents a web-based tool for owners to create and publish annotation microtasks and workflows to execute them.

ToolScape[23] is a work that deserves prominence, as it is strongly related to the approach presented in this paper. ToolScape integrates simple annotation tools in which workers can perform a sequence of three microtasks, that was used to extract the step-by-step structure of the instruction videos, one of these tools is shown in Figure 3.

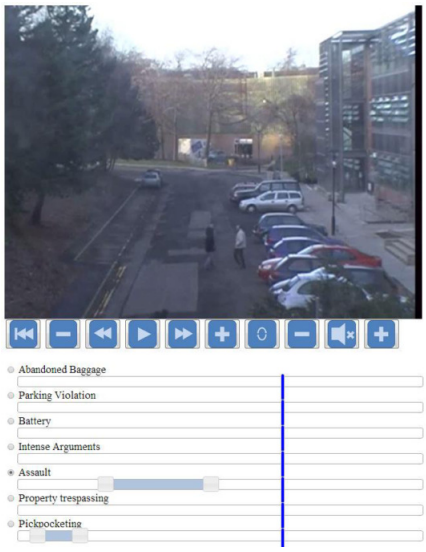

Figure 2: Simple surveillance annotation tool[15]

Moreover, is presented a design pattern to define the workflow for these tasks.

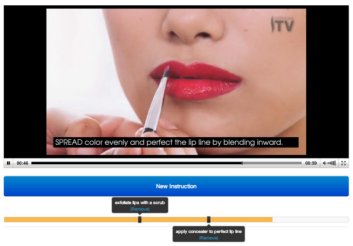

Figure 3: ToolScape annotation tool[23]

This brief discussion about some related works aims mainly to highlight the characteristics of the microtasks, as well as the simple annotation tools used to execute them.

5 CROWDNOTE

5.1 Method

Full Paper Webmedia 2017 [3] The crowdsourcing video annotation approach presented in this paper follows three steps: Preparation, Annotation, and Presentation.

The preparation step describes how a complex annotation task can be divided into simple microtasks, in addition, is presented a workflow for the activities required before the annotation step, such as to define what should be annotated and the annotation types, as well as to design the microtasks and the simple annotation tools to execute them. In the annotation step, the annotation microtasks are performed by crowd workers, that are the contributors to the process. This step follows a workflow in which each microtask is followed by a specific aggregation method that generates a result so that the output from a task feeds the next one. The presentation step displays the outcome delivered by the annotation step, also at this point, all partial results are available to be used in other applications. The approach introduced also allows the development of expansive video annotation systems in which it is easily possible to add new microtasks to improve its result or generate new results.

These steps contain specific activities and are executed sequentially how can be seen in Figure 4.

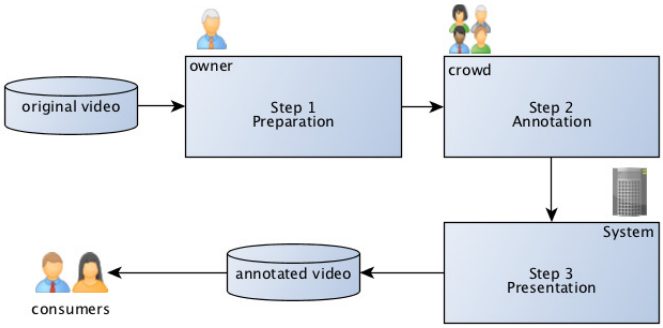

Figure 4: Process workflow

Preparation: all activities involved in this step are performed by the owner, who started the video annotation process. At this step is determined what must be annotated, also how they should be annotated. In this way the owner must determine:

(1) What kinds of point of interest should be annotated.
Ex: events, objects, subjects, issues.
(2) What annotation type will be used for each of these kinds.
Ex: free write, item selection, button click, image upload.
(3) What data type will be collected for each annotation type.
Ex: plain text, location, image, video.

To illustrate this point, the example of the football(soccer) match annotation will be recalled. In a football(soccer) match video the kinds of point of interest correspond to events such as goals, cards, and faults. For each point of interest observed it should be collected its kind, and the instant when this event happened. The annotation type to be used on the annotation tool can be a set of icons related to each event. Finally, the data type collected in this case may be plain text that contains the kind of event identified and the instant it happened [32].

Also, it is important to provide explanations or guidelines that can instruct the workers about how to execute the microtasks. An additional activity on the Preparation step is to determine what section of the video should be sent by each worker, this division can be made by duration (ex: send a 5 seconds segment to each worker), or using contextual criteria such as to send to each user a segment that contains a single dialog. The activities sequence for this step can be observed in Figure 5.

Annotation: An essential aspect of this step is to determine the microtasks' workflow, so the output from a task is taken as input by the next one, generating an outcome at the end of the last microtask. This cascade workflow is illustrated in Figure 10. It is important to notice that each task cell in composed by two activities, the microtask in self and the aggregation method, that generates the output from the obtained contributions. In this way,

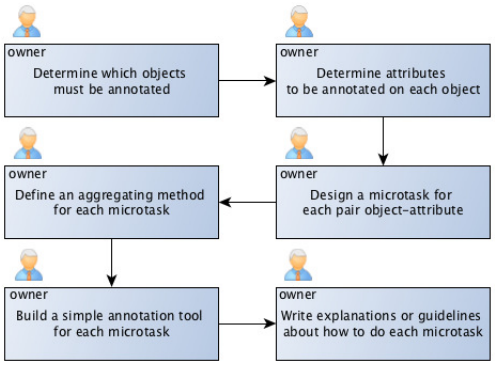

Figure 5: Preparation step

the output from the last task cell is the outcome provided by the system.

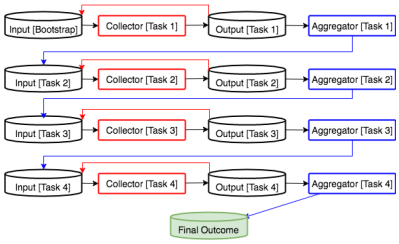

Figure 6: Annotation step for N microtasks

Presentation: at this step is generated an annotated video including the original video and the final outcome from the previous step. Other activities that can be proceeded at this step is to generate or to render, media items selected from the crowd annotations, as well as aggregate these items over the videos to compose a multimedia presentation.

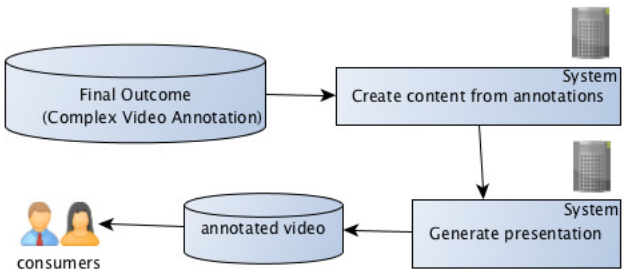

Figure 7: Presentation step

5.2 Framework

WFA Webmedia 2017 [2]

CrowdNote was developed as a classic Web system. To facilitate the sharing of all produced software, only technologies that do not require complex infrastructure were adopted. The Server was fully developed in NodeJS for easy deployment, the Client was developed in HTML 5 to improve compatibility, and the Database uses MongoDB as No-SQL database for flexible persistence.

The architecture of the CrowdNote is illustrated in Figure 8 in which is possible to observe the 3 main components: Server, Database, and Clients.

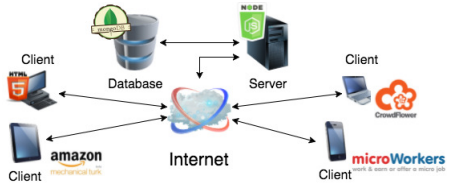

Figure 8: CrowdNote Architecture

5.3 The Server Component

The server system, illustrated in Figure 9, is composed of 3 modules: Collector, Aggregator and Player Provider.

- **Collector:** The Collector sends the jobs to the workers, receives the annotations from them, and stores the annotations into the Database. Information is exchanged between the Collector and the Client as JSON messages through HTTP requests for cross-platform compatibility.
- **Aggregator:** The Aggregator verifies, filters, groups, and processes the collected annotations of the crowd according to the rules defined for each task, and then stores the result in the Database.
- **Player Provider:** The Player Provider sends to the client the annotations, the extra content, and the original video. Thus, the player on the client can play the enriched video synchronously.

5.4 The Database Component

The persistence was addressed using MongoDB, which delivers a very attractive solution to build No-SQL databases with some characteristics that meet the crowdsourcing requirements such as high write load, high availability in an unreliable environment, easy scaling and partition, heterogeneous data into the same collection.

In this model, JSON document collections are used instead of tables, and the documents in each collection may have a different structure to store different attributes. This feature allowed the modeling of a very simple database structure, composed of 3 collections of documents. It was possible because documents in the Input and Output collections can contain different fields according to the task that consumes or generates the entries.

The Video collection stores entries related to the video segments dataset, the Input collection stores the input entries to the tasks, and the Output collection stores the contributions collected from the crowd. The result of the aggregation for each task is stored in the Input collection to be used by the next task, supporting the cascading tasks approach.

5.5 The Client Component

The client consists of simple forms-based annotation tools and a player capable of playing video and extra content synchronously.

The client has been fully developed in HTML5, in the simplest way possible. For each task, a simple annotation tool was created to collect contributions.

The Client communicates with the Server through JSON messages and HTTP requests so that they can be deployed on different systems and sites or even on crowdsourcing platforms such as Amazon Mechanical Turk, Crowdflower and Microworkers [12], as long as the JSON structure is respected. By using these platforms, the search and reward of workers are delegated to them, however, there is a financial cost involved in doing so.

5.6 Workflow

The 3 main components of CrowdNote communicate through data flows from **A** to **G**, as can be seen in the workflow in Figure 9.

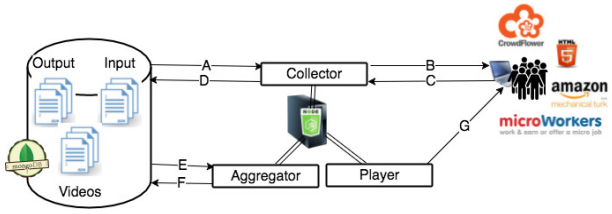

Figure 9: CrowdNote Workflow

- **A:** To generate each job to be sent to a worker, the Collector receives an entry from the Input Collection and the corresponding entry from the Videos Collection.
- **B:** The Collector sends a job to an instance of the Client, to be executed by a worker.
- **C:** The Client sends to the Collector the annotation made by the worker for the job received.
- **D:** The Collector stores in the Output collection the annotation collected from a worker.
- **E:** The Aggregator receives from the Output collection all annotations collected for a given task.
- **F:** The Aggregator stores the resulting entries from the aggregation process in the Input collection so that they are supplied as input to the next task.
- **G:** The outcome of the cascade of microtasks is sent by the Player Provider to the client so that it can play the video synchronously with the extra content.

6 CASE STUDY

CrowdNote is an environment that provides a collection of annotation tools, aggregation methods, and persistence models that can be selected, sequenced, and modified to generate different types of crowdsourcing applications based on video annotations. In order to create a system based on this environment, it is necessary to define the required microtasks sequence, and then select and specialize the resources provided by CrowdNote.

To demonstrate its working was built an instance of CrowdNote which consists of a system for video enrichment by adding extra content provided by the crowd. In this system, contributors are responsible for identifying the points of interest in the video, suggesting what content should be associated with each one, deciding the best suggestion for each point of interest, and finally deciding the best position in the video to present each content.

The extra content suggested by the crowd are images, text boxes, Wikipedia content, and Youtube videos, and the result delivered by this system is an enriched video, that consists of the original video presented synchronized with the extra content provided and selected by the crowd.

The approach taken to achieve the complex annotation needed to enrich the videos is to cascade microtasks that collect simple annotations, instead of collecting complex annotations for each contribution. In this way, people without specialization or training can contribute to the process.

- **Task 1 - Identify the points of interest** in the video that should be associated with the extra content. The first microtask is to send video segments to the worker and ask him to identify in this segment something that he believes deserves to be highlighted or supplemented. The aggregation rules for this microtask are to temporarily group the annotations with a tolerance of 0.5 sec, to count and to merge similar annotations in each group, and to determine for each time group which is the predominant point of interest in the annotations.
- **Task 2: Provide extra content suggestions** for each point of interest. In the second task, the worker receives a point of interest and should suggest extra content related to it. This content can be a text, an image, a YouTube video or a Wikipedia page. The aggregation of the second task consists in grouping the contributions by a point of interest and joining similar contributions to avoid duplicity.
- **Task 3: Ranking the suggested content** provided by each point of interest. In the third microtask, the worker receives a point of interest and the content suggestions for it. The contributor should choose the most appropriate content for the point presented. The aggregation rule for this task is to select the most popular content for each point of interest.
- **Task 4: Determine the positions** to display the extra content associated with each point of interest. In this task, the worker receives an item that represents a point of interest and chooses the position in the video most suitable to display it. The aggregation method for this task calculates the average coordinate for each item to be displayed in the video.

6.1 Cascading Microtasks

The adopted approach consists of dividing the complex annotation into simple annotations that can be collected by a set of simple annotation tools. Each of these simple annotations is collected by a microtask.

As is illustrated in Figure 10, the input for each task is generated by the Aggregator after the previous task, except for the task 1. For this task is provided a bootstrap Input that is a list of video segments provided by the owner, that is who initiate the process. Each entry of the bootstrap input can represent a semantic block of the video.

Other applications that use CrowdNote may use different strategies to segment videos such as fixed time-length, SRT files, or even add a microtask to segment videos.

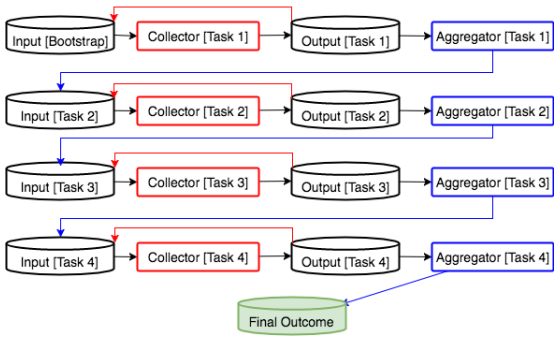

Figure 10: Cascading Microtasks

6.2 Task 1

Identify Points of Interest: The first annotation microtask is supported by the tool represented in Figure 11, collecting identification for points of interest. In this task, the contributor receives a segment of video that should be watched, and if was found any point of interest, it should be marked and briefly described. These points of interest can be gestures, words, expressions, facts, concept, characters, events or anything that can be related to extra content.

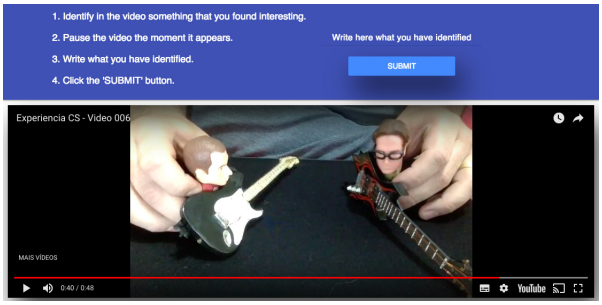

Figure 11: Annotation Tool for Task 1

6.3 Task 2

Provide extra content suggestions: The second task took as input the aggregated result from the task 1 that is a list of points of interest identified by the workers. This microtask is supported by the annotation tool represented in Figure 12. This tool presents to the worker a point of interest and the video segment positioned at the moment it occurs. This way, is possible to use the video for reference and contextualization.

Through this tool, the worker can contribute by writing a text related to the point of interest, sending an image or sending a link to a YouTube video or a Wikipedia page.

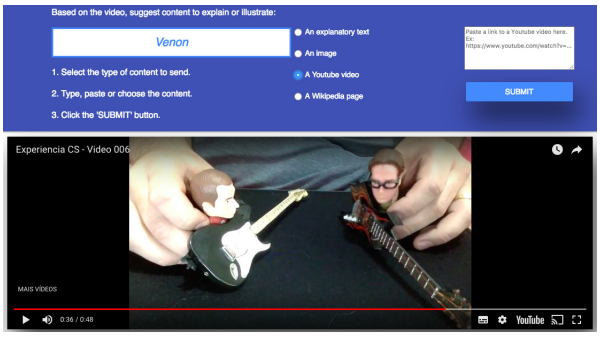

Figure 12: Annotation Tool for Task 2

When the collection of contributions for this task is done, the Aggregator groups the content of the sender by a point of interest, and then joins the similar suggestions. In this way, a list of points of interest with a set of content suggestions for each is added to the next task, without repeated suggestions.

6.4 Task 3

Ranking Suggestions: The third task receives as input the list of points of interest, with the content suggestions for each of them. For each job, the annotation tool illustrated in Figure 6 shows the worker a point of interest and the video positioned at the time that point occurs. The annotation tool displays the content suggestions for that point of interest below the video, so is possible to browse through the content to choose the most appropriate one.

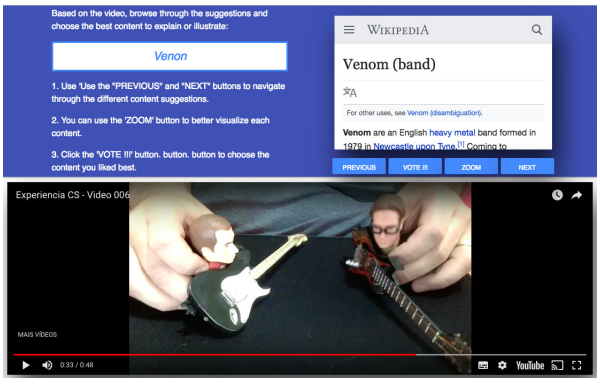

Figure 13: Annotation Tool for Task 3

The worker can enlarge each content to see it better, how can be seen in Figure 14. In addition to playing the videos as a suggestion of content.

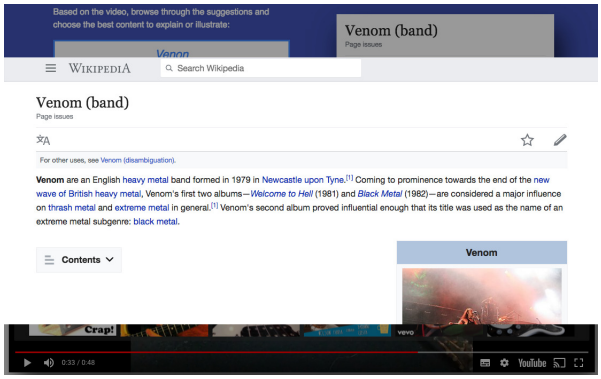

Figure 14: Annotation Tool for Task 3 - Zoom

The aggregation process for this task counts the votes for each content suggestion and chooses the most popular content for each point of interest.

6.5 Task 4

Determine the positions: The last task receives as input the list of points of interest and the content chosen to associate with it. For each job, the tool shown in Figure 15 shows the worker the video that is positioned at the time the point of interest occurs and the reference item for the content selected in the video.

The contribution to this task is to suggest the best position to present the extra content, using the annotation tool to determine this position. The tool allows the worker to change the position of the items in the video by clicking the desired point. Among the 4 microtasks, this is the fastest and easiest to perform.

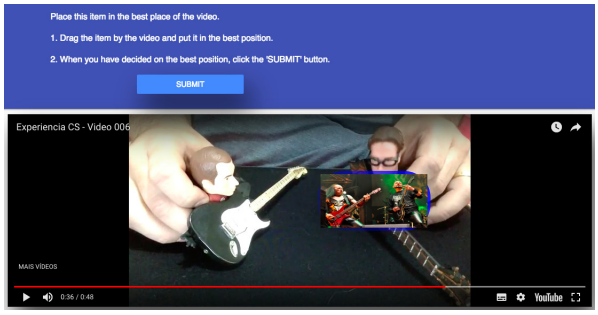

Figure 15: Annotation Tool for Task 4

Following the studies about the wisdom of the crowd, the strategy to determine the correct position is to calculate the average coordinate of the contribution for each content [16]. In this way, the aggregation process calculates the average coordinate of the items, based on the contributions of the crowd. The result of this process is the position where each item related to a point of interest will appear in the video.

6.6 Player

The presentation system, shown in Figure 16, receives the video, extra content, and necessary metadata from the Player Provider. This system is capable of reproducing the original video synchronized with the extra content, that is displayed every time a point of interest happens in the video. Is important to remind that all extra content displayed with the video was provided, selected and positioned by the crowd.

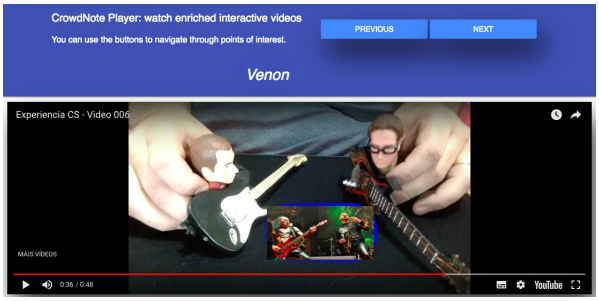

Figure 16: Displaying an extra content item over the video

When the user clicks on some extra content displayed in the video, the presentation is paused and a larger preview of the selected content is displayed in a zoom box. This system features navigation by extra-content instead of the traditional timeline navigation, making available a button-bar with buttons to navigate among the extra contents.

7 FINAL REMARKS

This paper introduced a crowdsourcing approach to annotate videos without requiring experts, trained workers or time-consuming tasks. Moreover, was conducted an experiment to validate it by generating interesting annotated videos that could be used to create interactive multimedia presentations. To support this experiment was developed a toolkit that includes the presentation system, and a set of video annotation tools and aggregation methods.

During the annotation stage, it was noticed that the faster microtasks received more contributions, because the workers contributed more times, annotating more items. One conclusion about this is that volunteers use to dedicate a set time to perform tasks, so they were willing to execute any number of microtasks during that interval.

Another observation about the approach is that the cascade of tasks results in the generation of partial results that can be used for other purposes. For example, content suggestions that have been collected to annotate the video can be used to populate an online dictionary or encyclopedia.

Moreover, the individual aggregation of the result of each microtask allows an adequate processing for each annotation, as well as specific validations for them.

Perhaps one of the most interesting results was to see if this approach is capable of generating systems that can be reused and expanded. This can be observed when the first presentation system was generated and later a new task was added in the process, allowing the construction of an improved presentation system.

In addition to the approach presented, which was able to guide crowdsourcing annotation processes with a certain degree of complexity, a system was also generated that demonstrates how this approach can be applied. This system is available for use and can be used both to replicate this experience and to perform other works.

7.1 Next Steps

An immediate improvement in the system includes changes in the aggregation methods of tasks 1 and 2. Currently, the similarity comparison uses simple syntactic techniques for content analysis. However, a method is being developed that performs these comparisons through morphosyntactic analysis.

The owner module will also be developed, which will allow this system to be used even outside the academic environment. Currently, the system counts only as microtask execution module, which was necessary to perform the experiment.

This work also served as a starting point for a series of projects that will be developed shortly. In particular, the approach presented will be refined to become a complete method.

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