

## Automated Indexing and Search of Video Data in Large Collections with *inVideo*

<sup>1</sup> Shuangbao Paul Wang, <sup>2</sup> Xialong Cheng, <sup>3</sup> Carolyn Maher, <sup>4</sup> William Kelly

<sup>1</sup> Metonymy Corporation, Fairfax, Virginia, 22030, USA

<sup>2</sup> George Washington University, Washington, DC, 20052, USA

<sup>3</sup> Rutgers University, New Brunswick, NJ, 08901, USA

<sup>4</sup> Metonymy Corporation, Fairfax, Virginia, 22030, USA

<sup>1</sup> Tel.: 703.628.7936

<sup>1</sup> E-mail: paul.wang@computer.org

Received: 1 June 2017 /Accepted: 7 August 2017 /Published: 31 August 2017

**Abstract:** In this paper, we present a novel system, *inVideo*, for automatically indexing and searching videos based on the keywords spoken in the audio track and the visual content of the video frames. Using the highly efficient video indexing engine we developed, *inVideo* is able to analyze videos using machine learning and pattern recognition without the need for initial viewing by a human. The time-stamped commenting and tagging features refine the accuracy of search results. The cloud-based implementation makes it possible to conduct elastic search, augmented search, and data analytics. Our research shows that *inVideo* presents an efficient tool in processing and analyzing videos and increasing interactions in video-based online learning environment. Data from a cybersecurity program with more than 500 students show that applying *inVideo* to current video material, interactions between student-student and student-faculty increased significantly across 24 sections program-wide.

**Keywords:** Video processing, Video index, Big data, Learning analytics, Education.

### 1. Introduction

Big data analytics are used to collect, curate, search, analyze, and visualize large data sets that are generated from sources such as texts (including blogs and chats), images, videos, logs, and sensors [1]. Video data is a major format of unstructured data, and should be an indispensable area of big data analytics. However, most analytics tools are only effective in analyzing structured data. Due to the nature of the special file format, traditional search engines hardly penetrate into videos, and therefore video indexing becomes a problem [2–13].

Videos contain both audio and visual components, and neither of these components is text based. To understand a video, viewers must actually play it and use their eyes and ears to analyze the sounds and

visuals being presented to them. Without watching a video, it is hard to glean information from its content or even know whether there is information to be found within. Existing search engines and data analytics tools such as Google, SAS, SPSS, and Hadoop are effective only in analyzing text and image data. Video data, however, are difficult to index and therefore difficult to analyze.

In education, video presents a large opportunity for both classroom and online education [14]. In addition, video is a great teaching format because it can be both more enjoyable and more memorable than other instruction formats [15]. Furthermore, video instruction allows for students to work at their own pace, for teachers to be able to teach more students, and for more reusable teaching materials to be available when compared to an in-person lecture.

MOOC (Massive Open Online Courses) creators realize the many benefits of video, as evidenced by the prevalence of video in MOOCs. Many MOOCs focus on video files for the bulk of their instructional material so it is clear that the MOOCs of the future must also focus on videos.

*inVideo* [16], developed under a US Department of Education grant, is able to analyze video content (language and video frames) prior to initial close researcher review of the video. A highly efficient video indexing engine can analyze both language and video frames based on natural language and referent objects. Once a video is indexed, its content becomes searchable, and statistical analysis as well as qualitative analysis are possible. Commenting and tagging add a layer of hyper-information and therefore increase the accuracy of the transcript, which was automatically extracted from the video by the *inVideo* tool. The indexing technology is especially useful in mining video data in large video collections. *inVideo* also has an automatic caption system that can transcribe the words spoken in the video. Instructors can use the tool to construct in-place video quizzes for assessments.

Learning is an integration of interaction. The interaction might exist between learners and instructors or between learners and computers. While the traditional approach would be to analyze grades at the end of the semester, this lacks the benefits that come from interactions that occur during the course [17]. As an increasingly large number of educational resources move online, analyzing interactions between students and online course material is becoming more important. Many learning management systems (LMS) have built-in learning analytics tools to look into the data [18–20]. Due to the limitation of the data gathering and indexing, the built-in tools are generally not sufficient in assessing study outcomes, especially for video content.

## 2. Related Work

Automatic video index and search have wide applications in education, public security, and many other video-intensive areas.

An airport traffic and security monitoring system constantly indexes videos gathered from surveillance cameras and searches for the suspect based on the graphical and textual information provided by the authority [9].

A video content indexing and retrieval tool indexes digital videos automatically on 34 hours of TV news broadcast. The sampled frames are then used in providing the basis for various analyses [21].

Big data and learning analytics can become part of the solutions integrated into administrative and instructional functions of higher education [22]. Traditional face-to-face instruction supports a traditional data-driven decision-making process. Videos as a form of big data are more extensive, and particularly time-sensitive, learning analytics

application. It is important that instructional transactions are collected as they occur.

Learning analytics can provide powerful tools for teachers in order to support them in the iterative process of improving the effectiveness of their course and to collaterally enhance their students' performance [23]. Dyckhoff developed a toolkit to enable teachers to explore and correlate learning object usage, user behavior, and assessment results based on graphical indicators. This learning analytics system is able to analyze data such as time spent, areas of interest, usage of resources, participation rates, and correlation with grades data, and visualize them using a dashboard. However, the system is unable to analyze the interactions between students and the online learning systems on videos.

In order to analyze videos for various applications, we have developed a video index engine to look at every word spoken in the video and categorize it using our custom index algorithm. In addition, a content-based pattern recognition engine can search individual frames of the video to recognize objects and individuals being displayed. The collaborative commenting, tagging, and in-place quizzes make videos more accessible and also increase the accuracy of the search engine [7-8], [10].

## 3. Video Indexing and Search Algorithm

Videos are a different data type than text and images, in that they are unstructured data. Traditional search engines are mostly text based, with a few tools that allow for searching of images. In order to index a video, a search engine needs to extract meaningful language from the audio and convert it to text, while simultaneously converting the visual frames into a series of images that can be used to recognize persons and objects in the video. This is an extremely difficult task, given that videos are a compound format. Not only are the audio and visual components integrated, but also within each of these components there is a blend of information being presented in a manner that cannot be distinguished as easily by a computer as by a human brain. For example, the audio of the file may contain speech, music, and background noises that a computer will have a hard time recognizing and analyzing.

### 3.1. Automatic Indexing Algorithm

The video indexing engine uses the vector space model to represent the document by a set of possible weighted content terms. The weight of the term reflects its importance in relation to the meaning of the document [24].

After calculating the normalized frequency of a term in the document, the weight to measure the relative importance of each concept or single term is obtained. The automatic index algorithm then calculates the final position in n-dimensional space.

The result is to be used for generating search results or visualization.

### 3.2. Searching Videos by Keywords

Video search involves two steps: analyzing by keywords and analyzing by image references. When a keyword is entered, the system looks through the indexed audio transcript to see if there is a match. An image reference may refer to either a picture or keywords that describe an object in the video using an appropriate semantic space. Video clips whose language contains the keywords will be retrieved. Fig. 1 shows how indexed videos can be searched using keywords in the spoken language.

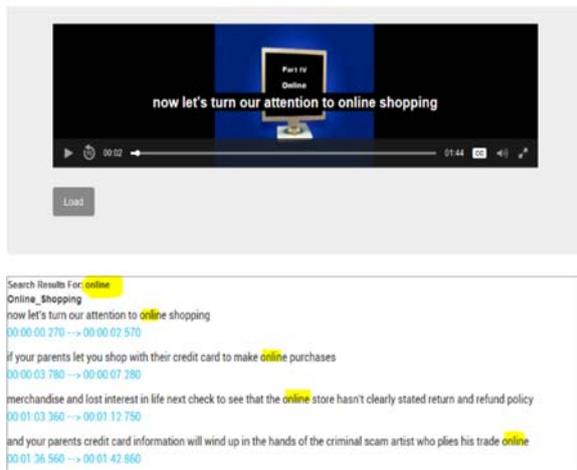


Fig. 1. Analyzing Videos by Keywords.

### 3.3. Searching Videos by References

Searching videos by references examines the frames of the video to see if the given picture or keyword is found. If the reference is a picture, then the system uses a Content Based Image Retrieval (CBIR) algorithm to find the match frames and return the video clips that contain the reference picture. Fig. 2 shows the image-based CBIR algorithm that retrieves the video frames corresponding to the reference picture (at the bottom).



Fig. 2. Analyzing Videos by Image References using the CBIR Algorithm.

If the reference is a keyword (e.g. credit card) then the system uses a knowledge tree to find matches in the video. If one video frame contains an object matching the features associated with the keyword, the section of the video is returned. Fig. 3 shows how a search for the keyword credit card will retrieve the video frames that contain objects as credit cards.



Fig. 3. Analyzing videos by Keyword References using a Knowledge Tree.

### 3.4. Searching Videos in Multiple Languages

Sometimes multiple languages may be found in videos. Transcription engines normally only work in one language or in closely related languages. For other languages, a different transcription engine may be required. *inVideo* addresses this problem by allowing videos with different languages to be searched from a single user interface. The *inVideo* system does not translate between languages. It only transcribe based on the language of original videos. For example, a Chinese video will result in a transcript in Chinese. Fig. 4 shows the indexing engine properly analyzing the Chinese language.

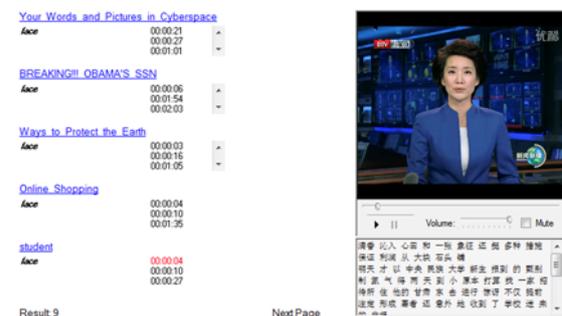


Fig. 4. Analyzing Videos with Different Languages.

When entering the word “student” in Chinese, the video search engine will locate that term in the transcript and return the corresponding frames. Currently, there are multiple languages that can be analyzed by the *inVideo* system, with more to be added.

### 3.5. Elastic Search and Content-Aware Elastic Search

Elastic search makes the *inVideo* application capable of searching video data across distributed environments with HTTP protocol and schema-free JSON documents. Elastic search makes it possible to expand the community by deploying a pluggable cloud architecture, configurable automatic discovery of cluster nodes, persistent connections, and load balancing across all available nodes. Video collections under ACE are no longer restricted to a particular video collection. More importantly, there is no need to move other video collections in a centralized site, which is merely feasible anyway.

Indexed videos can be searched by keywords. When a keyword is entered, the cloud system searches its generated transcript of the audio files to find matches. Video clips whose audio track contains the keywords are retrieved.

The enhanced elastic search partitions videos into individual frames. Thus, users also have the ability to search a video by examining the video frames to see if a given object is found. The enhanced elastic search algorithm matches contents in the frames and returns the video clips that contain the reference objects. This process allows us to combine images and words to create hybrid metadata.

For instance, in mathematics education, there is interest in studying the representations students make. The CBIR algorithm allows us to search the videos for particular representations that a student would make, such as images of rods, blocks, or tree diagrams. Students may construct these models without talking about them, and thus an audio transcript would miss it. By being able to search the frames of the video, a user interested in tracing a student's construction or explanation of a representation can query the database. If a frame of the video contains an object matching the particular representation, this section of the video is returned.

### 3.6. Machine Learning and Cloud-based Data Analytics

It should be noted that the goal of the software is not to reproduce the word-for-word accuracy of a human-generated transcript of video files. Rather, the goal is to determine the extent to which voice-to-text analysis and image analysis are able to retrieve desired sections of the video for enriched human analysis. The critical task is for the system to identify a sufficient amount of relevant hits that pertain to the search reference terms or images. Search queries have advanced from keywords to natural language. The *inVideo* software uses artificial intelligence and machine learning technologies to analyze videos and use big data analytics tool to explore, index, and visualize videos. *inVideo* also has security features that secure data and communication in the cloud and protect privacy [2-6, 11-12].

### 3.7. Transcript Time-Stamping

*inVideo* also includes a Transcript Time-stamping System (TTS), a new software tool built by the research team, which turns traditional video transcripts generated by external transcription methods into time-stamped transcripts, which can be incorporated into the *inVideo* application. The TTS application adds timestamps to existing transcripts and formats them in a way that is amenable to video search through the *inVideo* platform. The application is semi-automated; when a timestamp is keyed to a word, the software calculates the time allotted for all surrounding words, so that all the non-keyed words are aligned between timestamps in a reasonable approximation of their occurrence in the audio track. Subdividing each sentence and introducing additional cycles for the algorithm to run on smaller segments of the transcript can increase the accuracy. Fig. 5 shows the timestamp creation process:

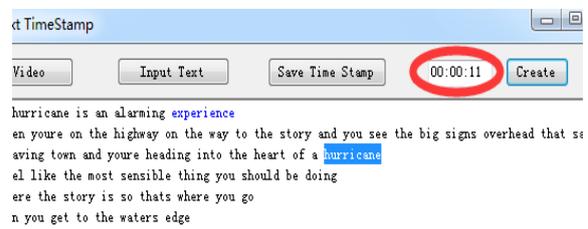


Fig. 5. Automatically calculating timestamps.

## 4. Collaborative and Interactive Learning

Automatically generated video transcripts may have accuracy problems. Besides, the vast numbers of videos in MOOCs make them impossible to be retrieved correctly with just one or a few simple keywords. To solve these problems, we have implemented a collaborative filtering mechanism that includes commenting, tagging, and in-place quizzes. These features improve accuracy and increase interactions between students and the online learning systems. With collaborative filtering, learning resources retrieval on MOOC systems is greatly improved, and better student achievement is therefore expected.

### 4.1. Collaborative Filtering

Collaborative filtering is a process of improving accuracy of the automatic indexing algorithm by leveraging user feedback. This is popular on websites that have millions of users and user-generated content. Users are able to create time-stamped comments on videos. These comments can be hidden or made public so that someone else who views the video can see the comment at a specific time. These comments help

increase accuracy of the search tool and transcript and enhance interactions in online learning.

Tagging on videos is another implementation in the *inVideo* system. It is to attach keyword descriptions to identify video frames with categories or topics. Videos with identical tags can then be linked together, allowing students to search for similar or related content. Tags can be created using words, acronyms, or numbers. This is also called social bookmarking.

A search term usually yields many related results, which in many cases are hard to differentiate. Commenting and tagging add additional information, refine the knowledge, and increase the video search accuracy. At a time when information is exponentially growing, these features are extremely helpful for students to obtain the knowledge with the least amount of time.

#### 4.2. In-place Assessment with iQuiz

Internet computing has the advantage of employing powerful CPUs on remote servers to provide applications across the network. *inVideo* comes with an Internet Computing- based video quiz system (iQuiz) to utilize the computational power of remote servers and provide video quiz services to users across the Internet. Currently, videos are mostly non-interactive, and thus there are no interactions between students and the learning content. Students either view videos online or download them to their personal devices. There is no way for educators to know whether a student has understood the content or even to know whether the student has viewed the video or not.

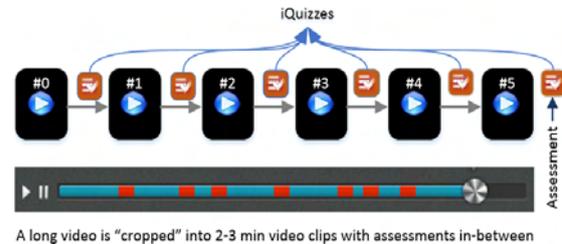
iQuiz can be used to assess learning outcomes associated with video study. Quizzes can be embedded into videos at any place where an instructor wants to assess the outcome of the student's study. iQuiz runs as a service on servers. This enables users to execute this resource-intensive application with personal computers or iPads, which would not be possible otherwise.

Instructors can enter into the authoring mode where they can write quizzes by indicating the start and stop positions on the video and adding questions. Video quizzes are stored in XML format, and are automatically loaded while students are watching the video in the learning mode. Answers to the quizzes, either correct or incorrect, are also stored in the XML database for immediate assessments. Assessment of adaptive learning on videos provides better outcomes for students than the traditional video content study with little or no feedback [25].

#### 4.3. Transform Linear Videos into Interactive Learning Objects

Videos are linear in nature. This structure is hardly interactive, nor does it contain branches. Using the

*inVideo* tool, classical videos can be transformed into a series of video clips with assessments in between and at the end. Through this process, the video-based learning material becomes interactive. Fig. 6 shows a test that we conducted, which turned a 46-minute video into six selected 2-3 minute video clips. The red segments on the stage bar are the samples, so it is clear that not all video content was used in the samples.



A long video is "cropped" into 2-3 min video clips with assessments in-between

Fig. 6. Transform Linear Videos into Interactive Learning Objects.

### 5. Experimental Results

#### 5.1. Classroom Interventions

To test the *inVideo* system, we selected the 20 most recent videos from National Science Digital Library (NSDL) in cybersecurity and used the *inVideo* tool to extract keywords that appeared in the transcripts. From this set, we selected the top two ranked keywords: Target (data breach) and encryption (using encryption to secure data). We were confident that those two keywords made good discussion topics that could increase classroom interactions.

As a result, we added two discussion topics to the Masters of Science in Cybersecurity program for Spring 2014 (24 class sections; each section has 25 students on average).

Videos lack interactions between learners and the online learning environment. Even worse, videos above a certain length will likely never be watched at all, because students cannot easily determine what content is within it or how to locate that content. To address this issue, we used the *inVideo* tool to index the content and break the large videos into a series of small video clips. By doing so, we made it possible for students to watch short video clips covering individual key concepts directly, while retaining the ability to view the whole video if necessary. This served to not only increase student interest and engagement in the lesson, but also, more importantly, to improve their ability to comprehend and retain information.

Student responses and interactions can be used as a proxy for their degree of engagement with any particular part of the course. As one example of how the *inVideo* indexing served to increase this measure, consider Week 2 of the class. In our assessment of past offerings (pre-*inVideo*) we discovered that this part of the course is a quiet week, because the individual assignment starting in the week will not be due until

Week 8. This meant that the interactions in the classrooms dropped significantly from Week 1. Based on this assessment, we decided to use the *inVideo* intervention in an attempt to generate more interactions during Week 2 of the course.

Our initial observation of one class was very promising; the total number of responses, defined as each posting after viewing a video clip, for Week 2 reached sixty-eight, as compared to only two for the same week in the previous semester. This initial finding encouraged us to investigate the results for all twenty-four sections program-wide. Fig. 7 shows the number of responses for the 24 sections comparing Fall 2013 to Spring 2014 during Week 2.

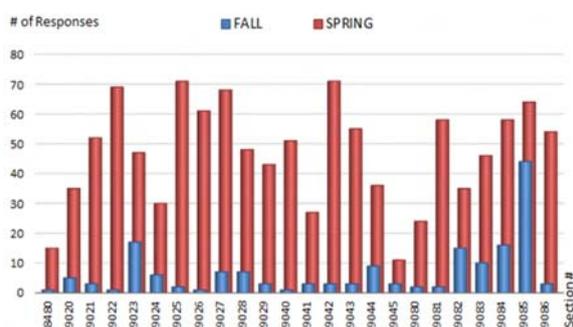


Fig. 7. Number of Responses for 24 Sections – Week 2 Discussions.

For the research we conducted, Week 2 student responses across the 24 sections were almost seven times higher during Spring 2014 (1,129 responses) than during Fall 2013 (164 responses).

For the cybersecurity online/hybrid class, we have five graded discussions, one individual assignment, one team assignment, and two lab assignments. Two more hands-on exercises (labs) have been added since Spring 2014. Data from the team projects, using the same intervention method, show that student-student and student-faculty interactions were 6.5 times greater for the courses with the *inVideo* intervention (104 responses compared to 16 responses). We also measured student performance against desired learning outcomes. The average grades on both team projects and final grades was higher in Spring 2014 than in Fall 2013. Here we see that the index and data analytics tool *inVideo*, in combination with just-in-time assessment and intervention, improved learning outcomes.

Based on our finding, we are in the process of breaking up every large learning module into several learning objects using *inVideo*. The new competency-based learning objects will be used to construct the knowledge cloud. These new learning modules will consist of many competency-based learning objects, and will be more interactive, rational, and accessible.

We will use *inVideo* to expand the scope of this research to other activities in courses within the cybersecurity program. This tool could also be useful to courses in other disciplines. Using the *inVideo* tool,

linear videos are transformed into a series of interactive learning objects. This is vital in an online learning environment where interactions and learning outcomes are valued the most.

## 5.2. RBDIL Study and Accuracy Factors

The *inVideo* system has also been tested on the Robert B Davis Institute for Learning (RBDIL) mathematics education video collection at Rutgers University. The collection features decades of classroom video tracking a cohort of students as they learn mathematics over the years. This collection has been used extensively throughout the testing and refinement of the *inVideo* system.

One interesting outcome of the RBDIL research has been on the nature of videos and how certain factors impact index accuracy. Through our experiments, we found that some videos have very low accuracy rates (10 %) for transcripts created using *inVideo*, while others had significantly better results ranging from 40-90 % and above. We conducted a study to determine what the main contributing factors were that cause the inaccuracy in certain files. The team consulted with senior engineers at the National Institute of Standards and Technologies (NIST) and other professionals in the area. Using signal-processing technology, we analyzed the video signals and discovered interesting results.

Videos with significant ambient noise or unclear signals are known to have accuracy problems, and one of our key findings in this study has shed light on video attributes that would lead to decreased accuracy in a given sample. By investigating this phenomenon further and identifying possible methods to counteract these mitigating factors now that we are aware of their influence, we have been teaching the *inVideo* software to improve its outcomes with those videos featuring one or more confounding attributes.

To this end, we compared different videos to observe which factors are primarily involved in affecting the accuracy, and have worked to create methods for counteracting these factors. Fig. 8 and Fig. 9 show the frequency and quefrequency distributions for two videos: one with an acceptable level of indexing accuracy and one with one or more mitigating factors that confound accurate indexing.

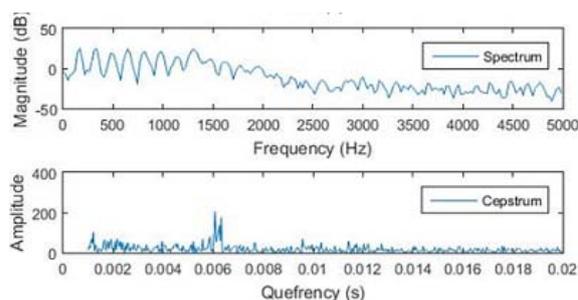


Fig. 8. Signal analysis for video with 90 % accuracy.

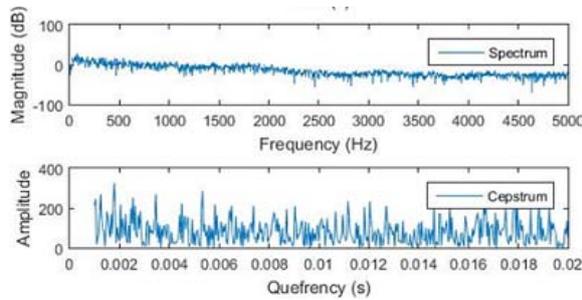


Fig. 9. Signal analysis for video with 10 % accuracy.

Our study shows that ambient noise (reflected through the quefrequency) plays an important role in the accuracy of the transcripts. Ambient noise may come directly from the environment or from the natural distortions that can occur due to recording practices, such as the reverberation that results when the distance between vocal and microphone is not ideal. Acceptable tolerance levels for distance-based reverberation will vary based on the type of microphone used. This supports our conclusion that the type of recording equipment used and the methods by which it is deployed is one of several key factors in determining accuracy.

Based on these results, the team conducted experiments in which the voices were re-recorded on select videos and the resulting audio track was layered back to the original videos. For these tests, the team used a condenser microphone and took steps to ensure that it was directed optimally in relation to the source and within an acceptable distance. As expected, the accuracy improved from less than 20 % to 80 % or above.

It is worth noting as well that there is a distinction between ambience and signal clarity problems when it comes to human and computer comprehension. Many instances of poor signal quality are obvious to the human observer, because the information will be hard to understand. However, the human brain is quite good at inferring meaning in less than ideal signals in ways that computers can't accomplish as easily. There exists a range of issues that may exist in a video file that can create issues for automated indexing and search, despite appearing acceptable to a human viewer. Any researcher or educator creating video content would be wise to consider this.

## 6. Conclusion and Future Work

This paper discussed a novel video index and analytics tool used to analyze video data. Video indexing engines analyze both audio and visual components of a video, and the results of this analysis provide novel opportunities for search. To improve accuracy, we can either improve the transcription engine, analyze video frames better where there is no audio, or crowd-source accuracy through collaborative filtering. For transcription accuracy, one potential

accuracy improvement can come from using a self-learning artificial intelligence (AI) system that could be taught to recognize certain accents or languages. The process or requirements for instituting such a system and the magnitude of the improvement in accuracy are to be studied in the future.

At present, the *inVideo* tool is limited to only analyze native (non-streaming) videos. We will continue our research on analyzing live videos and streaming videos and make *inVideo* available to broader video collections and applications.

## Acknowledgements

This research is funded in part by grants from the US National Science Foundation (NSF) [EAGER-1419055 and DGE-1439570].

## References

- [1]. K. Bakshi, Considerations for big data: Architecture and approach, in *Proceedings of the IEEE Aerospace Conference*, 2012, pp. 1–7.
- [2]. S. Wang, Dual-data defense in depth improves SCADA security, *Signal*, 2016, pp. 42–44.
- [3]. S. Wang, W. Kelly, Smart cities architecture and security in cybersecurity education, in *Proceedings of the Colloquium of Information Systems Security Education (CISSE)*, 2017.
- [4]. P. Wang, W. Kelly, A novel threat analysis and risk mitigation approach to prevent cyber intrusions, *The Colloquium for Information System Security Education (CISSE)*, Vol. 3, Issue 1, 2015, pp. 157–174.
- [5]. S. Wang, A. Ali, W. Kelly, Data security and threat modeling for smart city infrastructure, in *Proceedings of the IEEE International Conference on Cyber Security of Smart Cities, Industrial Control System and Communications*, 2015, pp. 1–6.
- [6]. S. P. Wang, R. S. Ledley, *Computer Architecture and Security: fundamentals of designing secure computer systems*, Wiley, 2013.
- [7]. S. Wang, W. Kelly, J. Zhang, Using novel video indexing and data analytics tool to enhance interactions in e-learning, in *Proceedings of the World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education (E-Learn)*, 2015, pp. 1919-1927.
- [8]. S. Wang, A. Ali, J. Zhang, W. Kelly, *inVideo* - a novel big data analytics tool for video data analytics and its use in enhancing interactions in cybersecurity online education, *WIT Transactions on Information and Communication Technologies*, Vol. 60, 2015, pp. 321-328.
- [9]. S. Wang, J. Zhang, A video data search engine for cyber-physical traffic and security monitoring systems, in *Proceedings of the IEEE/ACM Fourth International Conference on Cyber-Physical Systems*, 2014, pp. 225–226.
- [10]. S. Wang, W. Kelly, *inVideo* - a novel big data analytics tool for video data analytics, in *Proceedings of the IT Professional Conference*, 2014, pp. 1-19.
- [11]. S. Wang, R. Ledley, Modified Neumann architecture with micro-OS for security, in *Proceedings of the*

- China-Ireland International Conference on Information and Communications Technologies (CICT'07), 2007, pp. 303–310.
- [12]. S. Wang, F. Shao, R. S. Ledley, Computer - A framework of intrusion-free secure computer architecture, in *Proceedings of the International Conference on Security & Management (SAM'06)*, Las Vegas, Nevada, USA, June 26-29, 2006, pp. 220–225.
- [13]. A. Serrano-Laguna, J. Torrente, P. Moreno-Ger, B. Fernandez-Manjon, Tracing a little for big improvements: Application of learning analytics and videogames for student assessment, in *of the Fourth International Conference on Games and Virtual Worlds for Serious Applications (VS-GAMES'12)*, Genoa, Italy, October 29-31, 2012, pp. 203–209.
- [14]. V. J. Rideout, U. Foehr, D. Roberts, Generation m2: Media in the lives of 8- to 18-year-olds, 2010. <http://kaiserfamilyfoundation.files.wordpress.com/2013/01/8010.pdf>
- [15]. H. Choi, S. Johnson, The effect of context-based video instruction on learning and motivation in online courses, *The American Journal of Distance Education*, Vol. 19, No. 4, 2005, pp. 215–217.
- [16]. S. Wang, M. Behrmann, Video indexing and automatic transcript creation, in *Proceedings of the 2<sup>nd</sup> International Conference on Education Research*, New Orleans, LA, 2010.
- [17]. T. Elias, Learning analytics: Definitions, processes and potential, 2011, <http://www.learninganalytics.net/LearningAnalyticsDefinitionsProcessesPotential.pdf>
- [18]. C. E. Hmelo-Silver, C. A. Maher, A. Alston, M. Palius, G. Agnew, R. Sigley, C. M. Mills, Building multimedia artifacts using a cyber-enabled video repository: The VMCAnalytic, in *Proceedings of the 46<sup>th</sup> Hawaii International Conference on System Sciences, HICSS'13*, Wailea, HI, USA, January 7-10, 2013, pp. 3078–3087.
- [19]. C. E. Hmelo-Silver, C. A. Maher, G. Agnew, M. Palius, S. J. Derry, The video mosaic: design and preliminary research, in *Proceedings of the 9<sup>th</sup> International Conference of the Learning Sciences (ICLS '10)*, Chicago, IL, USA, Vol. 2, June 29 - July 2, 2010, pp. 425–426. [Online]. Available: <http://dl.acm.org/citation.cfm?id=1854729>
- [20]. G. Agnew, C. M. Mills, C. A. Maher, VMCAnalytic: Developing a collaborative video analysis tool for education faculty and practicing educators, in *Proceedings of the 43<sup>rd</sup> Hawaii International Conference on Systems Science (HICSS-43 2010)*, Koloa, Kauai, HI, USA, 5-8 January 2010, pp. 1–10.
- [21]. C. A. F. P. Filho, T. A. Buck, C. A. S. Santos, An environment for video content indexing and retrieval based on visual features, in *Proceedings of the XV Brazilian Symposium on Multimedia and the Web (WebMedia'09)*, New York, NY, USA: ACM, 2009, pp. 25:1–25:8.
- [22]. D. M. Norris, L. Baer, Building organizational capacity for analytics: Panel proposal, in *Proceedings of the 2<sup>nd</sup> International Conference on Learning Analytics and Knowledge (LAK'12)*, New York, NY, USA: ACM, 2012, pp. 18–19.
- [23]. A. L. Dyckhoff, D. Zielke, M. Bultmann, M. A. Chatti, U. Schroeder, Design and implementation of a learning analytics toolkit for teachers, *Educational Technology & Society*, Vol. 15, No. 3, pp. 58–76, 2012, <http://www.ifets.info/downloadpdf.php?jid=56&a id=1257>
- [24]. S. Wang, J. Chen, M. Behrmann, Visualizing search engine results of data-driven web content, 2004, <http://www.w3.org/WAI/RD/2003/12/Visualization/VisSearch/VisualSearchEngine.htm>
- [25]. S. Wang, M. Behrmann, Automatic adaptive assessment in learning, in *Proceedings of the IADIS International Conference on Cognition and Exploratory Learning in Digital Age*, 2009, pp. 435–438.
- [26]. S. Wang, X. Cheng, C. Maher, W. Kelly, InVideo: An Automatic Video Index and Search Engine for Large Video Collections, in *Proceedings of the Second International Conference on Advances in Signal, Image and Video Processing (SIGNA'17)*, Barcelona, Spain, 21-25 May 2017.



**UFDC-1**

**Universal Frequency-to-Digital Converter (UFDC-1)**

- 16 measuring modes: frequency, period, its difference and ratio, duty-cycle, duty-off factor, time interval, pulse width and space, phase shift, events counting, rotation speed
- 2 channels
- Programmable accuracy up to 0.001 %
- Wide frequency range: 0.05 Hz ... 7.5 MHz (120 MHz with prescaling)
- Non-redundant conversion time
- RS-232, SPI and I<sup>2</sup>C interfaces
- Operating temperature range -40 °C ... +85 °C

[www.sensorsportal.com](http://www.sensorsportal.com) [info@sensorsportal.com](mailto:info@sensorsportal.com) SWP, Inc., Canada

