

Inaccessible Island vs Urban Education in Greece

Knowledge-Based Summarization of Educational Videos by Analyzing Students' Watching Patterns

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Abstract— During the last decade, the problem of inequality in education has been studied by several researchers, especially regarding urban and rural (inaccessible) areas. Most studies conclude that funding and adoption of new technologies are necessary to reduce inequalities. However they do not propose any specific means to overcome these inequalities. Towards this direction, in this paper a specific method is proposed that contributes to the reduction of inequalities, without demanding any funding. The method is designed especially for inaccessible areas (including isolated islands), which face network connectivity issues or Internet speed becomes very slow. In particular knowledge-based video summarization is introduced, to overcome boredom, frustration, anger etc. when students try to watch online educational videos, using limited throughput channels. The main question is: which information is less important so that it can be excluded or roughly described? In this paper students play the role of human sensors, by letting recording and analyzing their watching behaviors. Then average watching patterns are extracted and used for video summarization, which is accomplished by a key-frames extraction algorithm that detects uncorrelated content. Finally, results are presented, to delimit the potential of such applications as well as to set the bases for future work.

Keywords— inaccessible island, education, content summarization, network accessibility

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1. Introduction

Greece has around 6,000 islands and islets, 227 of which are inhabited. About the 1/4 of these islands are inaccessible, making the 132 primary schools [1] that are established on these islands, also inaccessible. Even though Greece is among the top 50 countries in the world regarding GDP per capita [2], it has never successfully eradicated its urban-rural disparity. Inadequate investment in rural education and especially in inaccessible island education has caused an urban-rural gap in children's educational attainment, school quality and returns to education.

This urban-rural disparity puts the population that lives in inaccessible islands into a poverty trap, where few economic resources and little human capital are allocated to help them break out. The majority of students cannot migrate to large cities such as Athens, Thessaloniki, Patras etc and receive the

highest possible quality of education, so that they do not get drawn back into the rural poverty trap.

There are several complaints and problems regarding education at inaccessible islands. Ms Kikili has served as a teacher at several primary schools located in inaccessible islands and has an extensive experience of these problems, most of which have been discussed with several of her colleagues, during the last decade. In particular:

- One major problem is the transportation of students from their villages to the nearby schools. Students and their families do not know how the transportation will take place and if the transportation will be available every day. In several cases parents are putting themselves through transporting their children to schools by their own means of transport. In other cases they pay for taxi, which burdens the family's budget.

- Another problem is that there are schools which do not have the necessary number of teachers. In this case students look for education outside of school (private lessons)
- In several cases teachers teach in many schools. There are times were teachers have to go from one school to another school during the break. Under these circumstances, teachers cannot get acquainted to students, they cannot follow the school life and have difficulties in teaching their lessons. This is the so called teacher-courier phenomenon.
- Students have to sit in a chair and hear their teachers for seven hours ! We ask children to withstand what an adult cannot.
- In some cases books are not well-written and they are difficult to teach. It is also difficult for students to read them.
- In some other cases books are written for students that live in urban areas, disregarding students that live in rural areas such as islands.
- Students are taught the English language for at least eight years but the school does not provide any certificate of foreign language knowledge. Again students have to resort to private lessons.
- Examinations are not related to the books that are taught at schools. Publishing houses as well as private education set the ground regarding examinations.
- New teaching methods could help even the weak students, but they are not used extensively.
- School books assume that teachers have the required technical and material support, something which is not true especially in case of inaccessible islands.
- It is very difficult to provide effective and sufficient education in classrooms with 27 or more students.
- Teachers that are near retirement are sometimes tired and not in the mood to teach “naughty” students.

Of course, all aforementioned problems cannot be solved at once and just by the means of Technology. Several other initiatives should be carried out (policies, governmental interventions, equipment supply, etc.) including technical solutions. In order to confront some of the abovementioned problems, this paper focuses on video, which is a significant educational tool. In particular, in several cases teachers suggest to students to watch online videos, in order to better understand a topic (e.g. a historical event, a geographic location, a chemistry/physics phenomenon etc.). However inaccessible areas (including isolated islands), face also connectivity issues or Internet speed becomes very slow. In this case, when students try to watch online videos, they are bored, frustrated, angry etc. due to the limited throughput. Some video material should be excluded from downloading, or roughly described. Video summarization is a scientific approach that tries to solve this problem. However the main question is: which information is less important so that it can be excluded or roughly described ? In this paper students

play the role of human sensors, where knowledge is gathered and used for effective video summarization. More specifically, students watch educational videos and their watching behaviors are recorded, without recording any personal information. We are just interested in watching patterns. Then average watching patterns are extracted and used for video summarization, which is accomplished by a key-frames extraction algorithm that detects uncorrelated content. Finally, results are presented, to delimit the potential of such applications as well as to set the bases for future work in the field of educational content summarization.

The rest of this paper is organized as follows: in Section II state-of-art work is presented. Section III presents the proposed summarization scheme, while Section IV provides experimental results. Finally Section V concludes this paper.

2. State of Art

Several works have been carried out in the past, to discuss various problems related to education at rural and inaccessible areas. In [3], based on publicly available large-scale survey data (RUMiC), logistic regression and survival analysis are applied to illustrate the new education-poverty trap imposed on migrant children by the institutional constraints and hierarchies in children's education, created by the Chinese household registration system in Chinese cities. In [4], ordinary least squares (OLS) regression, spatial filtering regression and geographically weighted regression (GWR) are integrated to explore determinants of student performance in Salt Lake County. Path analysis is used to examine the interactions among school performance, student background, and neighborhood environments. The authors find that over 60% of the variation in student performance can be explained by school resource, student background and neighborhood environments. The GWR model further reveals that student performance in the eastern region with a higher percentage of whites, higher household income and higher education levels, is more sensitive to the neighborhood environment than in poorer and more diversified northwestern regions. Finally, path analysis finds that household income and population density influence student performance indirectly by attracting more whites to the neighborhoods. In [5] the authors try to offer a solution to the seemingly unending challenge of bridging the gender disparity in education in Nigeria. The paper discusses the merits of women education, women education in Nigeria, barriers to women education in Nigeria, open and distance learning, the merits of open and distance learning (ODL) and finally, the role of ODL in increasing access to education in Nigeria. In [6] the study states that amount invested seems insufficient to reduce education inequality for West African countries to catch-up with the desired skill, knowledge and growth. The researchers suggest that UNESCO should have a higher rate of education expenditure as a ratio of GDP for education financing in the annual government budgeting. In [7] the authors try to understand the local geographies of British Internet use, showing that the area with least use is in the North East, followed by central Wales. Their most interesting finding is that after controlling for demographic variables, geographic differences become non-significant. The apparent geographic differences appear to be due to differences in demographic characteristics. In [8] the authors aim to determine the level of convergence of local government budgets in Indonesia. Using statistical estimation models, and data covering of 33 provinces in Indonesia, the

study finds that the convergence on total revenue will occur on all Indonesian regions for a long time but not in education spending. The policy implications on education in Indonesia are different across regions. In [9] inequality of opportunity in higher education is explored. The authors assess the determinants of attaining higher education in Egypt, Jordan, and Tunisia and quantify the extent and drivers of inequality of opportunity. They find that inequality is similarly high in Egypt and Tunisia, but moderate in Jordan. In all three countries family socio-economic characteristics are the primary driver of inequality. Family characteristics affect attainment even after accounting for test scores, which are themselves influenced by socio-economic status. Particularly in Egypt and Tunisia, where higher education is free of charge, public spending on higher education is ultimately regressive. Thus, a theoretically meritocratic and equitable system perpetuates inequality. In [10] probit models are used to estimate the probability of senior high school graduates from different regions being enrolled in colleges, holding their socioeconomic background and year of graduation constant. Results show that there is significant difference among regions in the probability for colleges, but the difference in the probability of four-year colleges is only significant in urban context. The major difference exists between students from urban areas in the eastern provinces and students from all other sub-regions. In [11], the main objective of the study is to analyze the changing trends of social (education and health) inequalities before and after decentralization at the inter-regional and intra-regional level in Pakistan from 2005 to 2015. Coefficient of variation (CV) and decomposition of Theil inequality index are used to evaluate the spatial dimensions of inequality at the provincial and rural-urban level. Results of CV indicate high disparity in the education and health sectors at both inter-provincial and intra-regional level. In [12] the authors study the multidimensional disparity in elementary schools of the East and South Indian states in terms of gender gap ratio, literacy, enrolment and dropout rates. Besides, the study has also tried to explore the multidimensional disparity in educational attainment caused by scarcity of basic educational infrastructure and low educational expenditure therein. The study found that high disparity persists in government and private schools in terms of enrolment of both boys and girls among the states. The dropout rate is high in the East Indian states and less in the South Indian states. South Indian states are well ranked in comparison to East Indian states in terms of Educational Development Index (EDI). Excluding Karnataka, in all other states the recruitment of teachers has increased in the assessment period, but the percentage of teacher training during in-service has declined significantly. Due to different time-bound programs implemented by the state governments in both the regions, literacy and enrolment rates have increased significantly, but the multidimensional disparity is still a major concern today. In [13] two structural factors are examined, which have restricted educational development in Southeastern Turkey: land inequality and ethnic fractionalization/conflict. Until recently a semi-feudal structure persisted in the region with politically and economically powerful tribal leaders and large landowners called *ağas*. At the same time, the region has been the site of an ethnic conflict, which has been ongoing as an armed insurgency for over 30 years between Kurdish insurgents and the Turkish State. Using a province-level data set, the authors test the impact of land inequality, conflict and ethnicity on education investment and school enrollment for the period

1970-2012. They find that higher land inequality reduces the school enrollment rates due to budget constraints imposed on poorer households. However, the economic and political power of *ağas* in the region does not block education investments. Moreover, they find that although the armed conflict in the region did not directly hinder education investments, it did reduce school enrollment rates at middle and high school levels, while increasing enrollment at the primary school level. Finally, they find that provinces with higher percentages of Kurdish population received less education investment even after controlling for conflict and land inequality. In [14] the authors argue that children in low-income households are more likely to face a number of social challenges, including constrained access to the Internet and devices that connect to it (i.e., digital inequality), which can exacerbate other, more entrenched disparities between them and their more privileged counterparts. Although the American Academy of Pediatrics' new guidelines encourage clinicians to reduce children's overexposure to technology, the authors argue for a more nuanced approach that also considers how digital inequality can reduce low-income children's access to a range of social opportunities. In [15] the study sought to develop a new synthetic and analytical indicator, called Socio-educational Inequality Index (IDSED), composed of four indicators divided into two classes. The first class (per capita/ sampling) sets the Socioeconomic and Sociocultural Indicator and the second (school information) the indicator of infrastructure and resources and schooling. Based on the traditional techniques of decomposition of inequality measures, this index has the purpose of presenting to what extent the state education network of Tocantins reflects, in its structuring, the inequalities that are inherent and characteristic of the capitalist mode of production and, therefore, projects such inequalities in the result of its action.

All aforementioned studies conclude that funding and adoption of new technologies are necessary to reduce inequalities in education. However they do not propose any specific means to overcome the inequalities in education. This paper, in contrast to the majority of existing works, proposes a method that reduces educational inequalities and does not need any extra funding. In particular it introduces knowledge-based video summarization by examining watching patterns of students.

3. The Proposed Knowledge-Based Educational Content Summarization Scheme

In this paper and in order to summarize educational video content, students' watching behaviors are recorded and analyzed. Of course no personal information is recorded. The knowledge-based summarization algorithm only considers watching patterns. In particular and in order to explain watching behaviors, let us provide the following example: let us consider an educational video EV_1 of 180 seconds duration, with 25 frames per second (PAL). This means that the video consists of 4,500 frames in total, constructing the following vector:

$$F = \{f_1, f_2, \dots, f_{4,500}\} \quad (1)$$

Let us now consider a set of students S , containing 200 students:

$$S = \{s_1, s_2, \dots, s_{200}\} \quad (2)$$

Let us also consider that s_{115} watches EV_1 in a non-linear way. This means that the student can jump to any frame of EV_1 , go forward, go back, watch a group of consecutive frames etc. In this case the following example watching pattern WP could be recorded for s_{115} :

$$WP(s_{115}) = \{3(f_8-f_{52}), (f_{87}-f_{91}), f_{202}, 4(f_{407}-f_{623}), \dots\} \quad (3)$$

where $3(f_8-f_{52})$ means that s_{115} has watched the set of frames from f_8 to f_{52} three (3) times, the set of frames f_{87} to f_{91} one time, frame f_{202} one time, set f_{407} to f_{623} four (4) times etc.

By averaging the watching patterns of all students of set S , a knowledge pattern is extracted, which shows the most important parts of the educational video. Of course this knowledge pattern can change as S changes (e.g. by including new students). Additionally students tend to have different backgrounds, interests, knowledge etc. In this case a personalized scheme could be examined, which could considered students' clustering based on their behaviors' similarity. However this is out of the scope of this paper and could be investigated in future research.

Having detected the most important parts of an educational video and in order to generalize content access to students that have not watched the video yet, video summarization is accomplished by a key-frames extraction algorithm. More specifically, from each important part of the educational video, key-frames are extracted by minimizing a cross-correlation criterion, so that the selected frames are not similar to each other (so that to present the diversity of the whole part).

Let us denote by g_k the feature vector of the k th frame of an important part, with $k \in V = \{1, 2, \dots, N_G\}$ where N_G is the total number of frames of the given part. Let us also denote by K_G the number of key-frames that should be selected. In order to define a measure of correlation among K_G feature vectors, an index vector is first defined as:

$$x = (x_1, \dots, x_{K_G}) \in W \subset V_{K_G} \quad (4)$$

where

$$W = \{(x_1, \dots, x_{K_G}) \in V_{K_G} : x_1 < \dots < x_{K_G}\} \quad (5)$$

is the subset of V_{K_G} containing all sorted index vectors x which contain the frame numbers or time indices of candidate key-frames. Then, the correlation measure among the K_G feature vectors is given by the following equation:

$$\begin{aligned} R(x) &= R(x_1, \dots, x_{K_G}) \\ &= \frac{2}{K_G(K_G - 1)} \sum_{i=1}^{K_G-1} \sum_{j=i+1}^{K_G} \rho_{x_i, x_j}^2 \end{aligned} \quad (6)$$

where ρ_{x_i, x_j} denotes the correlation coefficient between feature vectors g_{x_i} , g_{x_j} , which corresponds to frames with numbers x_i and x_j . Function $R(x)$ takes values in the interval $[0, 1]$. Values close to zero mean that the K_G feature vectors are uncorrelated, while values close to one indicate that the K_G feature vectors are strongly correlated.

Based on the above definition, it is clear that searching for a set of K_G minimally correlated feature vectors is equivalent to searching for an index vector x that minimizes $R(x)$. Searching is limited in the subset W , since the correlation measure of the K_G features is independent of the feature arrangement. Consequently, the set of the K_G least-correlated feature vectors is found by:

$$\hat{x} = (\hat{x}_1, \dots, \hat{x}_{K_G}) = R^{-1}(x) \quad (7)$$

Unfortunately, the complexity of an exhaustive search for obtaining the minimum value of $R(x)$ is such that a direct implementation of the method is practically unfeasible. For example, about 264 million combinations of frames should be considered (each of which requires several computations for the estimation of $R(x)$) if we wish to select 5 representative frames out of a part consisting of 128 frames. For this purpose, we have proposed several different methods in the past [16] - [20]. In this paper we use of a guided random search procedure implemented by a genetic algorithm (GA) [21]. The algorithm converges to an optimal solution very fast (depending on the size of each important video part), extracting each time the key-frames that provide the best possible description of the video part.

A. # of Key-Frames per Part & Complete Summary based on Usage Knowledge

According to the aforementioned analysis, for each specific part, a number of key-frames is extracted based on correlation. However since the complete summary is an assembly of key-frames from all parts, how many key-frames per part should be extracted ?

To answer this question, in this paper a social computing approach is incorporated. In particular, let us assume that the complete summary should contain a known number of key-frames, say K_C , from n parts. If part #1 provides K_{G_1} key-frames, part #2 provides K_{G_2} , etc., then:

$$K_C = K_{G_1} + K_{G_2} + \dots + K_{G_n} \quad (8)$$

For simplicity reasons let us assume that part #1 has received L_1 average attention. Similarly clip #2 has received L_2 average attention etc.. Then the number of key-frames per part can be estimated by:

$$K_{G_i} = \frac{L_i}{\sum_{i=1}^n L_i} \cdot K_C, \quad i = 1, \dots, n \quad (9)$$

Equation (9) is a linear way to estimate the number of key-frames per part and does not favor the parts that have attracted more attention (e.g. in a non-linear way).

4. Experimental Results

In this section, we evaluate the performance of the proposed educational video summarization scheme. Since currently there are not any standard educational video datasets for the described or other similar scenarios, the proposed video summarization scheme has been evaluated on several educational video sequences available on Youtube. In particular 100 educational videos have been gathered of a total duration of 325 minutes and 25 seconds (an average of 195.25 seconds). These videos contain complicated content, with zooming, panning, complex camera effects, motion etc.



Fig. 1. One randomly selected frame from Vid#35 – Overall view.

Due to space limitations, visual results are presented for a 12 minutes and 21 seconds video (Vid#35). This video shortly describes the planets of our planetary system. Figure 1 illustrates one randomly selected frame, which provides a characteristic view of the video.

Next, for all videos, 58 students have been asked to interact with these videos. All students came from the primary education, with an average age of 9.3 years. The watching behaviors have been recorded and analyzed. The extracted key-frames for Vid#35 can be seen in Figure 2. As it can be observed there are more extracted frames for the video part showing the sun (3 key-frames). This is probably due to the fact that the relevant part seems very impressive and can better catch the attention of young students. Here it should also be mentioned that some parts of the video are not covered at all (e.g. from frame 968 to frame 1,488) since students' attention was very low. As it can be observed, the final summary describes with high efficiency the educational video's visual content, since almost all parts of the video are represented at least with one key-frame.

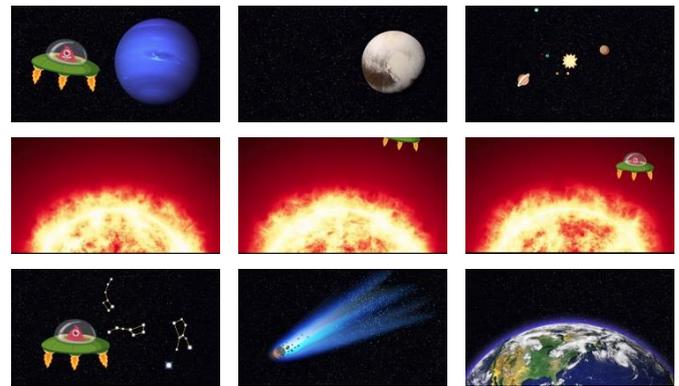
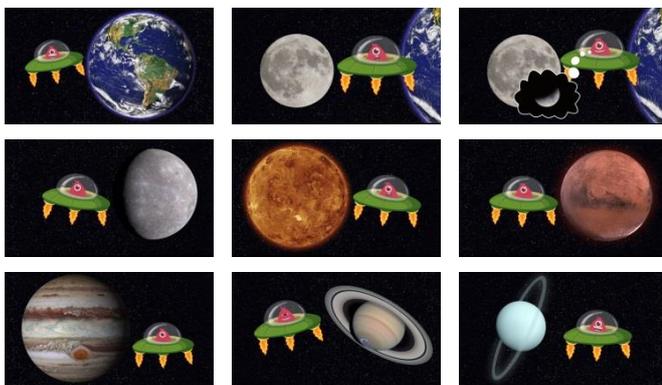


Fig. 2. The 18 key-frames extracted from Vid#35.

In Table I, the numbers of key-frames extracted for seven randomly selected educational video sequences are presented, along with transmission / storage reduction, which lies in the interval [99.78% 99.90%]. In the same table the computational cost is also provided. As it can be seen, in all cases, the required time is relatively low (about 0.19 seconds per frame on average or 4.75 processing seconds per video second). However, currently the algorithm cannot be incorporated in real time applications, but better meets the needs of offline knowledge-based summarization. Of course even if the algorithm could perform in real time, the application framework considers recording of the watching behaviors of several students. Thus without recording and analyzing behaviors (a process that cannot be performed in real time), the algorithm cannot work. Furthermore it should be mentioned that the average time per frame depends on the complexity of the content of each educational video.

Table I: Storage / Transmission reduction and computational cost requirements for five video sequences.

# of Video	Total # of Frames	Total # of Key-Frames	Transmission / Storage Reduction (%)	Average Comp. Cost per frame (sec)
8	9,865	13	99,87	0.17
19	18,265	19	99,90	0.20
35	18,525	18	99,90	0.19
47	21,200	25	99,88	0.22
62	5,787	11	99,81	0.15
79	6,934	15	99,78	0.16
93	23,675	34	99,86	0.24

Finally we have also contacted an experiment to test user satisfaction and check whether the proposed algorithm performs better than regular and random sampling. Towards this direction, for each one of the 100 educational videos (Vid#1 – Vid#100), two more summaries have been created, consisting of the same number of frames. For example for Vid#35, two more summaries have been created, each consisting of 18 frames. The first summary was created by regular sampling (e.g. in case of Vid#35, one every 1,029 frames was kept). The second summary was created by random sampling. Then our 58 users have been provided: (a) the summarized videos according to regular sampling, (b) the summarized videos according to random sampling and (c) the summarized videos according to the proposed knowledge-based summarization scheme. Each user was asked to express a viewing preference among the three

different summaries. The question was: “among the three summaries, which one do you prefer”. Here it should be mentioned that all users have watched all videos (during the first stage of our experimentation phase), thus they had an idea of the overall content of each video. It should also be mentioned that summaries did not have any hint about the producing algorithm and the presentation sequence changed so that not to affect the experiment.

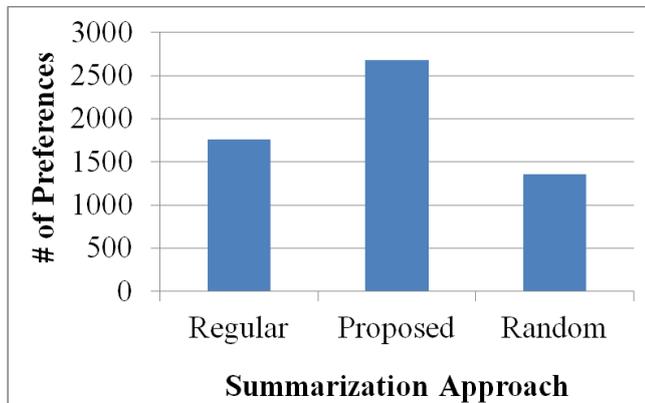


Fig. 3. Users' viewing preferences among three summarization approaches (Regular Sampling, Random Sampling and Proposed Summarization)

In total 5,800 preferences have been collected (100 preferences among 3 different summaries per user). Results are provided in Figure 3, where regular sampling has received 1,764 preferences (~ 30.4%), the proposed 2,678 (~46.2%) and random sampling 1,358 (~23.4%). As it can be observed differences are not very large. However there is a strong tendency of preferring the proposed knowledge-based summarization scheme. More specifically, among the 58 users 25 showed this tendency more explicitly (79% of their preferences among the different provided summaries were on the proposed scheme). However the other 33 users did not show such a clear tendency to mostly prefer the results of the proposed scheme. This is possibly due to the facts that: (a) summaries are just key-frames without containing any audio and (b) it was difficult to memorize the contents of 100 videos. Thus students could not easily recognize the representation quality of each summary, since they could not possibly remember the educational content.

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