AI/ML-Driven Content Repository Maintenance

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ABSTRACT

Accurate and relevant knowledge repositories are critical to all organizations and are especially vital to the United States Navy. Sailors' knowledge gaps or inaccurate content could cost the Navy billions of dollars and risk human life. Continuous updates to knowledge repositories are a well-documented strategy to avoid the obsolescence of knowledge management systems. In this work, we introduce an instructional content repository, a "YouTube for the Navy" that makes crucial content easily accessible and allows repository maintenance to keep content accurate and up-to-date. Repository maintenance can be laborious and prone to human error. To increase the accuracy of repository maintenance processes and reduce the need for human labor, our team is applying AI/ML-driven methods to automate and scale repository maintenance for the United States Navy. Leveraging Google Cloud Platform's Vertex AI video intelligence tools and custom algorithms developed by our Carnegie Mellon University partners, we outline several repository maintenance methods that will be tested with a Navy squadron during our Phase II STTR, including Tech Pub Alignment, Step Detection, and Step Order Detection.

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INTRODUCTION

Currently, aircraft maintenance training in the Navy is dominated by instructor-led schoolhouses. Official technical publications, which are a standing order, are used as a reference for maintainers as they do their jobs. Problematically, it is not feasible for schoolhouse training to build maintainer fluency in every aircraft maintenance procedure that they need to perform; even if there were time to do this, maintenance and repair procedures change over time. While maintainers can reference the official technical publication for a refresher on procedures that are new, or for which they've experienced skill decay, tech pubs lack the detail needed to show Sailors the nuance of performing a maintenance or repair procedure (Mayer, 2013). Video content, on the other hand, can depict in detail the nuanced tasks that the maintainer must perform on the aircraft. Video instruction has also yielded significantly higher learner performance in manual tasks when compared against text instruction (Donkor, 2020).

YouTube highlights the potential for crowd-sourced tutorial videos to be accessed on demand. Popular crowd-sourced videos are accessed as performance support for car maintenance, home repair, and other maintenance and repair tasks. Just as YouTube tutorial videos provide support to civilians performing car maintenance, vetted tutorial videos compliant with official tech pubs sourced from top-performing aircraft maintainers could support Sailors tasked with aircraft maintenance. Further, implicit steps not included in official tech pubs, as well as ways to ensure that a procedure has been effectively executed, could be included by top performers in tutorial videos, affording maintainers access to vetted "tips and tricks."

The benefits of affording Sailors access to tech pub-aligned, crowd-sourced tutorial videos can be seen in the high costs of maintenance errors. F/A-18 corrosion, which is greatly impacted by the effectiveness of maintenance procedures on the aircraft, cost the Navy over $2 billion between 2017 - 2020, per The Navy Times. By enhancing F/A-18 maintainer performance, billions of dollars could be saved while increasing aircraft uptime and safety. F/A-18 maintainers' effectiveness at handling new and complex procedures could be greatly improved with on-demand access to detailed tutorial videos aligned with official manuals. While official tech pubs are required to be used by maintainers, they are not detailed enough to instruct; tech pubs are necessary but insufficient.

While on-demand tutorial videos for aircraft maintainers would bring performance benefits, videos would also need maintenance to continuously ensure accuracy and alignment with official tech pubs. A suite of automated and human-in-the-loop content repository maintenance procedures to efficiently ensure that content is accurate, usable, and effective will be piloted with a Navy squadron during the Phase II STTR. The content repository maintenance methods described in the paper are a crucial component of the Step-by-Step Tutorial Engine for Performance Readiness (STEPR) platform, a tutorial-driven "YouTube for the Navy", that crowdsources best practices and makes them accessible to Sailors on demand.

BACKGROUND AND RELATED WORK

When designing an automated repository maintenance process using AI and ML-driven methods, it is essential to address the importance of knowledge sharing and previous approaches in content-based repositories. This section will discuss these aspects of repository maintenance along with existing digital video libraries for instructional and educational content, and diverse user-centered navigational techniques to improve repository maintenance.

Pure knowledge is sourced from the intellect of individuals, yet it is difficult to crystallize within tasks and instructional content (Davenport and Prusak, 1998). This type of knowledge is extremely valuable as workers can share their expertise and skills with other stakeholders, enabling them to recommend best practices for mutual learning (Chennamaneni et al, 2012). This type of collaborative knowledge transfer eliminates the need for production, service provision, and redundant learning costs (Hussain et al, 2016, Chennamaneni et al, 2012). Moreover, knowledge creation and transfer can also contribute to the success of an organization by deepening innovation potentiality (Hussain et al, 2016, Chennamaneni et al, 2012). However, it is an evident issue that effective knowledge sharing has not been optimized on an organizational level, especially within past knowledge management systems (Davenport and Prusak, 1998, Chennamaneni et al, 2012).

It is important to improve the maintenance of both personal and collaborative knowledge within an organization (Razmerita et al, 2014). Following the rapid popularity of social media, many companies have implemented the usage of social media for personal and collaborative knowledge maintenance (Razmerita et al, 2014). Ideally, social media is a platform, a collaborative environment for user-generated content creation and sharing, yet, content maintenance heavily relies on the individual creator (Razmerita et al, 2014). Ultimately, users both create and apply their content to knowledge repositories (Razmerita et al, 2014). For organizational purposes, the collaboration of knowledge sharing is highly emphasized, where workers share their knowledge to best practices and golden standards of a certain task (Razmerita et al, 2014). In response, organizations and corporations are trying to support these workers through knowledge management systems using social media (Razmerita et al, 2014). Consequently, there is still a need for optimal knowledge maintenance in effectively sharing the best practices derived from personal knowledge on a collaborative level.

Recently, there have been major developments in improving query performance within more advanced digital libraries and search engines, specifically for video instructional content. A study conducted by Salim et al. created an interactive application for volleyball trainers and players in receiving multimodal feedback for events of interest during training sessions and official matches (Salim et al, 2019). Detailed information on these events of interest, including these actions and objects, are stored and indexed in a custom repository within their interactive application, where users can filter through videos by a searched action, object, or event (Salim et al, 2019). This particular repository demonstrates the diverse forms in which data, particularly videos, can be stored in organized metastructures in which information can be extracted and identified. By organizing detail-sensitive data within a search engine, particularly videos, into organized metastructures, users can input detailed keywords and information to immediately receive relevant information specific to the users' needs.

While these approaches demonstrate promising results in repository creation and support, there is still a need for automated repository maintenance, especially for task-sensitive videos within the government organizations, such as the Navy. Further, content repositories that contain sensitive information need safeguards to ensure content accuracy and system security. Our research proposes a custom instructional content repository for Sailors within the Navy that is secure, reliable and accurate by automatically reflecting up-to-date changes and updates made to procedural content.

REPOSITORY DESIGN

The Knowledge Object (KO) data structures depicted below enable alignment between multiple media objects such as written technical publications and video tutorials. In KO repository design for the Navy, it is critical that the official technical publication is maintained as the primary source of information and that other attached media (such as videos) are aligned with the tech pub. To accomplish this, a KO has a nested data structure that contains high level information about the KO and the required steps or actions that are involved in the process that is being learned. Figure 1 shows the JSON structure that stores official steps using the organizational hierarchy of the written tech pub. Any change made by Navy officials to an official tech pub will be automatically updated in the tech pub's data structure through the STEPR update process.


```
{
    "id": "7.1.3",
    "title": "Volvo XC60 Drive Preparation",
    "manual": "MDART Version 2023 1.2.4",
    "steps": {
        "Tire Replacement":
        {"sub-steps":
            {
            "1": "Apply parking brake.",
            "2": "Remove the spare tire from the trunk.",
            "3": "Use wheel chocks to block the wheels opposite the one being changed.",
            "4": "Loosen the lug nuts on the wheel to be changed.",
            "5": "Raise the vehicle with a jack.",
            "6": "Remove the lug nuts and the wheel.",
            "7": "Install the new tire.",
            "8": "Screw the lug nuts back on.",
            "9": "Lower the vehicle.",
            "10": "Tighten the lug nuts."
            },
            "id": "III-7-2"
        },
        "Oil Change":
        {"sub-steps":
            {
            "1": "Park the vehicle on a level surface.",
            "2": "Turn off the engine.",
            "3": "Open the hood.",
            "4": "Locate the oil dipstick.",
            "5": "Pull the dipstick out and wipe it clean.",
            "6": "Reinsert the dipstick and pull it out again.",
            "7": "Check the oil level."
        },
        "id": "III-7-1"
        }
```


Figure 1. Example of a Knowledge Object in JSON format

Each media object, including the example video with a data structure depicted in Figure 2, has its data nested in a schema that specifies the official tech pub and step(s) aligned with the video. Each tech pub step demonstrated in the video is aligned with a distinct video moment that contains start and stop timecodes. The linkage of each moment in a video to the tech pub step demonstrated allows specific moments of videos to be flagged when a tech pub is updated, streamlining the video update process.


```
{
    "video-id": "1",
    "knowledge-object-id": "7.1.3",
    "knowledge-object-components": {
        "steps": {
            "Oil Change": {
                "sub-steps": {
                    "1": "Park the vehicle on a level surface.",
                    "2": "Turn off the engine.",
                    "3": "Open the hood.",
                    "4": "Locate the oil dipstick.",
                    "5": "Pull the dipstick out and wipe it clean.",
                    "6": "Reinsert the dipstick and pull it out again.",
                    "7": "Check the oil level."

                }

            }
    }
    },
    "video-title": "Volvo XC60 Oil Change",
    "video-description": "This video demonstrates how to change the oil in a Volvo XC60.",
    "video-url": "https://www.MARi.com/LearningActivities/watch?v=VolvoXC60OilChange",
    "video-length": "03:30",
    "video-moments": {
        "0": {
            "start-time": "00:00",
            "end-time": "00:30",
            "sub-step": "1"

    },
        "1": {
            "start-time": "00:30",
            "end-time": "01:00",
            "sub-step": "2"
```

Figure 2. Example of a Knowledge Object for a video object in JSON format

If a tech pub step or procedure is changed, aligned media objects are automatically flagged for human review. Further, the specific moments in a video impacted by a manual change are flagged to increase the focus and efficiency of human review of flagged videos. NLP methods (described in Maintenance Method 1, Case C) are leveraged to notify human reviewers whether a change to a tech pub step or procedure is moderate or severe.

REPOSITORY MAINTENANCE

The repository must ensure that instructional videos comply with their aligned tech pubs so that videos consumed by Sailors are accurate. As official tech pubs are revised periodically, continuous and automated content repository maintenance is needed to ensure that videos are updated in line with changes to aligned publications. Our AI-enabled and human-in-the-loop repository maintenance methods ensure that instructional videos are consistently aligned with official tech pubs while minimizing the human labor required to review videos. Figure 3 outlines the lifecycle of a tutorial video, including the maintenance methods that ensure content accuracy.

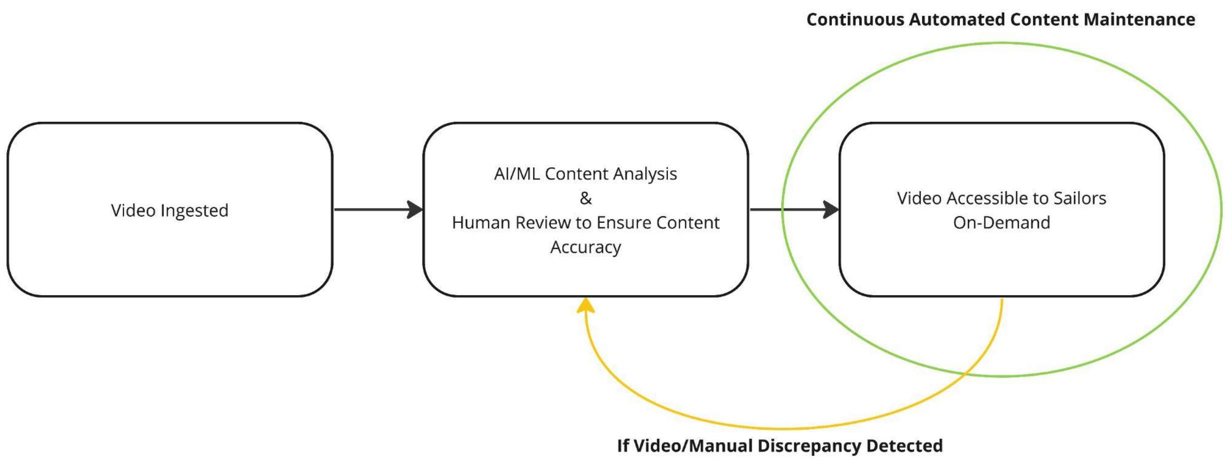

Figure 3. Tutorial Video Lifecycle

These repository maintenance methods complement the functionality of the STEPR platform, in which tutorial videos are uploaded, reviewed by AI and designated humans, and consumed on demand. Table 1 includes an overview of the three user experiences of the STEPR platform: Creator, Approver, and Consumer.

Table 1. STEPR Platform User Experiences

Creator	Approver	Consumer
• Upload Videos • View Output of Automated Content Analysis • Track the Video's Progress After it is Pushed to an Approver	• Confirm Whether the Video Accurately Demonstrates All Aligned Tech Pub Steps • Send Videos Back to Creator Organization With Comments • Approve Videos • Easily Reference the Official Tech Pub in the Platform UI	• View Videos On-Demand to Enhance Performance • Comment on Videos • Report Problems Observed in Videos

EXAMPLE TIRE CHANGE TASK WORKFLOW

To test the effectiveness of the repository maintenance methods, our team sourced nine publicly-available car tire replacement videos from YouTube on which to test our processes. The videos were selected for their on-screen demonstration and instructional narration of the majority of tire replacement steps in our gold standard manual. To serve as the gold standard, a sample "official" tech pub was created, modeled after Navy aircraft maintenance manuals from which to pull steps that should be demonstrated in each video. The use of tire replacement videos also allowed us to avoid the use of CUI or classified videos and use tutorial videos that depict a well-defined, step-by-step manual procedure. Table 2 consists of the steps that were included in the tire change procedure.

Table 2. Manual Steps in the Gold Standard Tire Change Manual

Manual Step Index	Manual Step
1	Apply parking brake
2	Remove the spare tire from the car
3	Use wheel chocks to block the wheels opposite of the wheel you're changing
4	Loosen the lug nuts from the tire
5	Loosen the jack
6	Use the jack to lift up the car
7	Remove lug nuts
8	Remove flat tire
9	Place the spare tire
10	Screw on the lug nuts
11	Use the jack to lower the car
12	Tighten the lug nuts

MAINTENANCE METHOD 1: AUTOMATED FLAGGING OF INCONSISTENCIES BETWEEN TECH PUBS AND ALIGNED MEDIA OBJECTS

When an update is made to the official procedure aligned with a tutorial video, the video is automatically flagged for review. Below, a description of STEPR's three use cases of automated inconsistency detection followed by human-in-the-loop review are detailed.

Case A: A new step is added to an official procedure aligned with a manual.

If a new step is added to an official procedure aligned with a video, the video is automatically flagged for human-in-the-loop review by our automated repository maintenance algorithms. In this case, the human Approver (designated by the user organization) will be alerted to the addition of a manual step to a video-aligned procedure. The Approver then reviews the video to determine whether:

I. The step is already demonstrated and no change is needed;
II. The video needs to be re-shot to include the new step;
III. Or, the video can be re-introduced to the repository with a warning message.

Case B: A tech pub step is removed from an official procedure aligned with a video.

If a step is removed from an official procedure aligned with a video, the video is flagged for review, and the start/stop timecodes of the removed tech pub step are referenced. In this case, the designated human-in-the-loop Approver reviews the step that was removed and determines which of the above-mentioned (see Case A) actions will deliver both efficiency and content accuracy.

Case C: A tech pub step aligned with a video is edited.

If a step in an official procedure is edited, the video is flagged for review and the start/stop timecodes of the edited manual step are referenced. NLP methods are leveraged to notify human reviewers whether a change to a tech pub step is substantive. Google Cloud Platform's Natural Language API and Vertex AI are leveraged to detect whether an edited tech pub step retained its meaning after being edited. For example, a manual step that is edited from "Apply 40 oz of sealant to the FIP seal underneath the wing." to "Use 40 ounces of sealant on the FIP seal under the wing." is flagged as a Moderate change. In this way, Approvers can easily direct their attention to the substantive edits that matter most. The definitions of "moderate" and "severe" can be flexibly altered in line with user needs.

The Approver is automatically notified that a tech pub step aligned with a video chapter has been edited. The below (Figure 4) notification informs the Approver that a Severe Change has been made to an aligned official procedure.

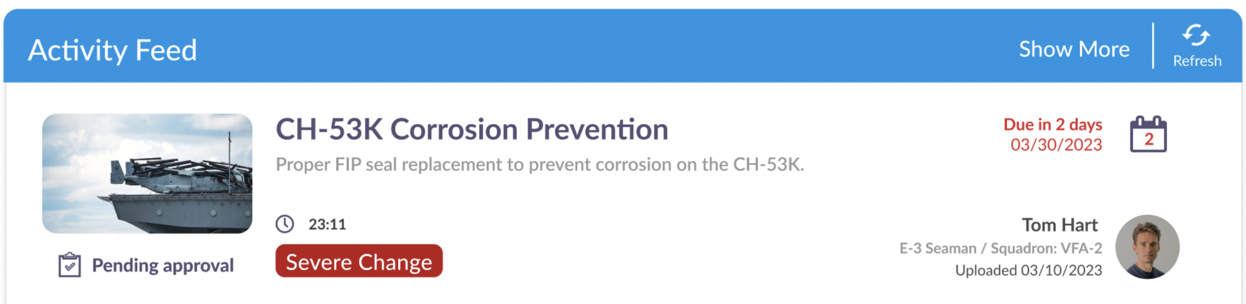

Figure 4. Approver notification to review a video.

MAINTENANCE METHOD 2: AUTOMATED LINKAGE OF TECH PUB STEPS AND VIDEO MOMENTS

When a video is uploaded into the media repository, the start and stop times of each aligned tech pub step are automatically identified, delivering time-savings and a check on potential human errors. Human labor required to label the start and stop times of each step is entirely removed or significantly reduced by automated identification of the start and stop times of each tech pub step. Further, this automated step identification process enables our system to detect whether a required tech pub step is missing from a video or is misordered (see Maintenance Method 3), alerting the video creator and allowing them to fix critical errors in the video before they push it to a designated human Approver. The Creator-facing automatic reminder to include all necessary tech pub steps in order ultimately saves Approver time, ensuring that Approvers do not spend their time identifying problems that can be caught by AI.

In the approach detailed below, the system automatically identifies the start and stop times of each tech pub step demonstrated in a video. The transcript of a video is stored as a word vector; a cosine similarity approach (enabled by the spaCy natural language processing library) is leveraged to match each tech pub step with the closest-matching section of the transcript's word vector. A human being has the ability to edit and override the output of this matching algorithm.

This approach was tested on nine car tire replacement videos sourced from YouTube, selected for their on-screen demonstration and instructional narration of the majority of tire replacement steps in our gold standard manual. The videos have a mean transcript length of 758 words and a mean time length of 6.96 minutes. When the transcript word vector comparison algorithm was run on the nine videos in a Google Cloud Platform virtual machine, the mean runtime taken to compare a transcript against the official manual was 43 minutes and 14 seconds.

Two human data labelers independently evaluated whether the algorithm identified each demonstrated step as occurring within its actual time of demonstration, using a shared data labeling protocol. The start of a tech pub step's demonstration was defined as the moment at which the video narrator begins describing the step or begins executing the step on screen, whichever comes first; the end of a step's demonstration was defined as the moment at which the video narrator finishes describing the step or completes on-screen execution of the step, whichever comes last. Table 3 lists the detailed results of the human labelers' evaluation of the matching algorithm's output. A tech pub step was considered to be identified by the matching algorithm if there was any overlap between the start and stop time of the step identified by the algorithm and those identified by the two human data labelers.

Table 3. For each video, which manual steps were demonstrated and which were identified by the matching algorithm as having overlapping start/stop times with human labels.

Video Number	Tech Pub Step Numbers Demonstrated in Video	Tech Pub Step Numbers Correctly Identified in Video by Algorithm	Proportion of Tech Pub Steps Identified in Video
video_1	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	3, 4, 5, 6, 8, 9	54.55%
video_2	1, 2, 4, 6, 7, 8, 9, 10, 11, 12	6, 7**, 12	30%
video_6	1, 3, 4, 6, 7, 8, 9, 10, 11, 12	1, 4, 7, 10, 11	50%
video_7	3, 4, 6, 7, 8, 9, 10, 11, 12	6, 7, 9, 11, 12	55.56%
video_8	2*, 4, 5*, 6, 11	6**	20%
video_9	1, 3, 4, 6, 7, 8, 9, 10, 11, 12	1, 3, 4, 6, 7, 9	60%
video_11	1, 2, 4, 6, 7, 8, 9, 10, 11, 12	1, 4**, 6**, 11, 12	50%
video_12	1, 2, 4, 6, 7, 8, 9, 10, 11, 12	1, 6**, 7, 9, 12	50%
video_13	1, 2, 4, 5*, 6, 7, 8, 9, 10, 11, 12	1, 4, 6, 7, 8**, 10, 12	63.64%

* = Only one labeler identified the demonstrated step in the video
** = Only one labeler identified a match between the demonstrated step and the algorithm-detected step

In order to confirm the quality of the human labelers, a Kappa statistic was computed, which indicates the degree of agreement between data labelers. The results of this analysis can be seen in Table 4. Generally, a Kappa value of 0.6 represents high agreement and a value of 1.0 represents complete agreement (McHugh, 2012). As can be seen in Table 4 the data labelers had high agreement on their identification of the steps. Note that video_8 is the exception with a score of zero, which occurred because this video was a partial video that did not include all of the steps.

Table 4. Kappa statistics validate the similarity of the two human labelers' assessment of whether there is overlap between the algorithm's identified start/stop time and the human-identified start/stop time of each tech pub step.

Video Number	Agreement (number of manual steps agreed upon)	Kappa Value
video_1	12	1.0
video_2	11	0.75
video_6	12	1.0
video_7	12	1.0
video_8	11	0.0
video_9	12	1.0
video_11	10	0.64
video_12	11	0.82
video_13	11	0.83

MAINTENANCE METHOD 3: AUTOMATED IDENTIFICATION OF MISSING AND MISORDERED STEPS IN VIDEOS

The matching approaches described above can also be leveraged to identify missing and misordered steps in a video. This automated safeguard ensures that videos discoverable by Sailors contain all necessary information in the required sequences. The cosine similarity algorithm leveraged in the two methods described above returns a similarity score between 0 and 1 for each match made. A threshold can be defined such that, for example, any tech pub step for which the highest similarity score for a start and stop time in a video is less than .4 is flagged by the matching algorithm as likely missing from the video. The value of the threshold can be adjusted as needed by the user organization. Further, the matching algorithms outlined above can be used to flag cases in which manual steps are demonstrated out of order. For example, if the third step in an official procedure is identified as occurring in a tutorial video before the second step in the official procedure, the video creator can be automatically notified that the video needs to be re-shot with steps in the proper order. This way, the video creator can eliminate errors before pushing the video to the Approver.

DISCUSSION AND CONCLUSION

In the context of the Navy, the performance benefits of on-demand, sailor-sourced tutorial videos can only be harnessed if they are accompanied by infrastructure that ensures content accuracy. The methods outlined in this research ensure that both AI and expert, human Approvers review content to verify accuracy before a video is made accessible to Sailors. Further, the automated repository maintenance methods save the human Approvers' valuable time, eliminating time spent identifying the start and stop times of manual step demonstrations. Initial algorithms can identify around ~48% of tasks demonstrated in videos, evidenced by the proportion of steps identified in videos by the STEPR matching algorithm, which will significantly reduce the time needed to administer and curate crowd generated videos.

It should be noted that the sample videos pulled from YouTube were not entirely made in alignment with the manual steps that were provided, yet our algorithms were still able to achieve success. As we continue to improve performance of our algorithms in both efficiency and step identification accuracy, the Creator-Approver process is expected to become significantly more efficient.

The STEPR system can enhance employee performance in any government or private sector organization with mission-critical, secure training needs. With use cases that span machine and vehicle repair to medical and emergency response procedures, AI and human expertise are leveraged in concert to ensure that detailed, accurate best practices are accessible on-demand to employees who need them.

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