US-Pro

An Application Enabling Efficient, High-Throughput Ultrasound Video Processing

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We describe a new graphical user interface–based application, US-Pro, designed to enable customized, high-throughput ultrasound video anonymization and dynamic cropping before output to video or high-efficiency disk storage. This application is distributed in a Docker container environment, which supports facile software installation on the most commonly used operating systems, as well as local processing of data sets, precluding the external transfer of electronic protected health information. The US-Pro application will facilitate the reproducible production of large-scale ultrasound video data sets for varied applications, including machine-learning analysis, educational distribution, and quality assurance review.

Key Words—informatics; machine learning; research; ultrasound video processing

Ultrasound (US) is an imaging modality that enables point-of-care medical evaluations without exposing patients to ionizing radiation.[1] Ultrasound provides diagnostic value in a multitude of clinical scenarios[2–6] and is increasingly considered a core component of future clinical practice, as evidenced by its introduction into residency and medical school curricula.[7,8] Furthermore, recent technical advances are likely to accelerate adoption of individual point-of-care use of US by reducing costs and device sizes.[9] As US demand and the number and variety of users increase, methods and technology to automate processes and enhance quality will become necessary.

Previous work has established methods for batch cropping US videos based on fixed pixels,[10] but this technique requires user conversion from the Digital Imaging and Communications in Medicine (DICOM) format and calibration for different transducer types and machines. In addition, since this method is built on cropping, it does not address the challenge of text and other data embedded in the middle of the clip. One algorithmic approach to US image anonymization had an anonymization success rate of 89.2% but was not available for testing.[11] This technique is limited by the use of US stills and therefore does not leverage the information contained in contiguous frames. Furthermore, none of the described approaches address the challenge of preparing US for subsequent machine-learning applications.[10,11]

Over the past few years, machine-learning techniques termed "deep learning" have come to prominence in image classification problems.[12,13] Prior studies have demonstrated the ability of deep-

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Abbreviations
DICOM, Digital Imaging and Communications in Medicine; ePHI, electronic protected health information; GUI, graphical user interface; HDF5, hierarchical data format 5; US, ultrasound

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learning networks to detect diabetic retinopathy in retinal fundal photographs,[14] classify skin lesions,[15] and diagnose pneumonia on chest radiographs at an expert level.[16] However, there have been few reports extending deep-learning techniques to US.[17,18] One key difference between US data and other radiologic modalities is that the clinical interpretation of US videos often requires the comparison of multiple frames. For example, in echocardiography, myocardial mechanics are assessed as a function of time.[19,20] Although deep learning has been applied successfully to videos,[21] extensions to US remain in the development stages.[20,22] Deep learning requires massive numbers of training samples, necessitating the use of automated preprocessing steps and efficient storage.

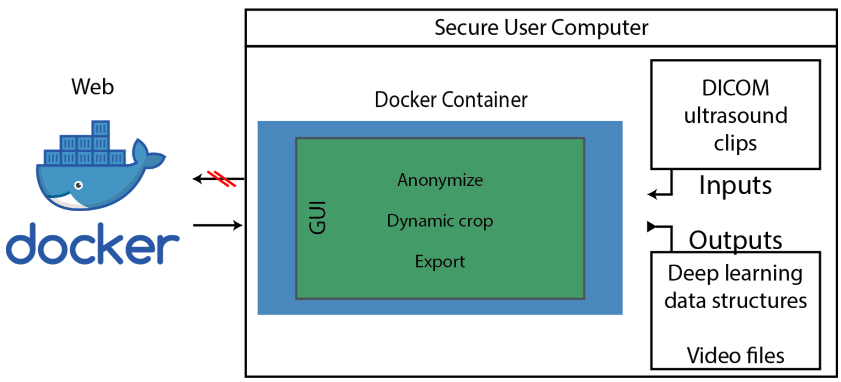
Given the widespread availability of machine-learning algorithms,[23–25] commoditization of computer resources,[26] and success of data crowd-sourcing competitions,[27] there is a strong incentive to mobilize large hospital system-based US video data sets for new clinical and research applications. We present US-Pro, a new graphical user interface (GUI)-based US video-processing application that reads DICOM-standard video files, optionally removes electronic protected health information (ePHI), and exports the data in one of many formats (Figure 1). To facilitate reproducibility and ease of use, we bundle the application into a single Docker container that contains all dependencies and libraries. We test the application on data captured on different US machines with an array of transducers to evaluate the generalizability of our approach. The US-Pro application has been made available to the larger scientific community via GitHub and the Docker image repository (online supplemental "Supporting Information").

Methods

This study was exempted from Institutional Review Board approval by the Yale Human Research Protection Program. Reproducibility and code access are key challenges in the adoption of new computational methods.[28,29] Application installation is managed via Docker; all dependencies and libraries are automatically downloaded (instructions in online supplemental "Supporting Information").[30] Docker containers are conceptually similar to virtual machines but have improved portability, have less computational overhead, and allow dynamic resource allocation.[31] The container includes all packages used, including SimpleITK for video decompression and processing, scikit-learn and numpy for image processing, and pickle, h5py, and skvideo.io for outputs, creating a one-step download for this application that ensures compatibility. All code is available on GitHub (https://github.com/adhaimovich/USPro).

To facilitate pipeline use, we developed a Django-based GUI written in Python that automatically communicates with the processing algorithms (Figure 2).[30,32] This GUI launches automatically when the user runs the container. At run time, the user is required to identify the local system folder, whose subdirectories contain the DICOM video files.

Figure 1. US-Pro deployment pipeline. Users download a publicly available Docker container before launching on host machines. Digital Imaging and Communications in Medicine clips are made available to the Docker container scripts, which process the data locally.



The entirety of the mounted data set is automatically processed as a batch on each execution.

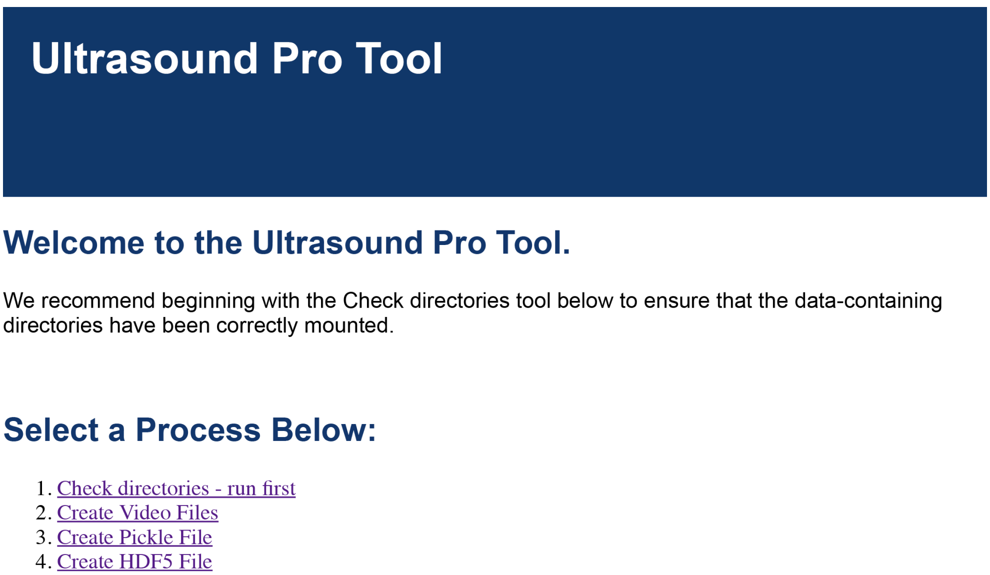
The DICOM clip-processing pipeline begins with decompression using the SimpleITK library, followed by conversion to gray scale. We then use an anonymization step, whose goal is to identify pixels representing common static elements, including image watermarking (eg, instrument model), ePHI (eg, patient identifiers), and scan information (eg, transducer type; Figure 3A). We first calculate the pixel-wise standard deviation over consecutive frames from a single clip. Pixels that are unchanged over the entire clip are reassigned a null value. The resulting cleaned image typically contains the prominent US cone and trace watermarking elements (Figure 3B). The dimensions of the cone are a function of manufacturer design as well as the transducer used in the medical study.[1]

We use image segmentation to dynamically identify the boundaries of the US cone.[33] The image is first binarized by using either a user-defined threshold value or Otsu's method[33] and then segmented by using contiguous pixel labeling (Figure 3C). The largest image segment is determined to be the US cone and used for cropping (Figure 3D). Bilinear interpolation is used to reshape the image to user-defined dimensions. Reducing image dimensions (eg, 600 × 800 to 256 × 256) with down-sampling saves disk space and processes images in preparation for deep-learning frameworks, which typically use smaller images.[34] This step is intended to facilitate transfer learning, ie, the use of pretrained image classification networks, which enables the efficient training of data sets containing fewer samples.[35]

The US-Pro application includes a number of output formats (Figure 1). First, US videos can be exported as video files viewable without a specialized DICOM interpreter to facilitate alternative analysis techniques and anonymized sharing. Alternatively, the US video contents can be exported as a Python-specific pickle file[36] or in hierarchical data format 5 (HDF5),[37] which is a high-performance, flexible data storage format that enables dynamic access while minimizing memory use.[37,38] Of note, both pickle and HDF5 are compatible with downstream deep-learning packages, including TensorFlow[25] and Keras.[23] Furthermore HDF5 data can be stored with lossless compression, including the gzip and Lempel-Ziv-Markov filters.[39] Data exported in this format are automatically reshaped to uniform user-defined dimensions. Descriptions of the output data structures used for these formats are provided in online supplemental "Supporting Information."

An assessment of software performance in anonymization and cropping was performed independently by 2 reviewers. Digital Imaging and Communications in Medicine videos were first converted to audio-video interleave formatting using the US-Pro tool

Figure 2. Software GUI.

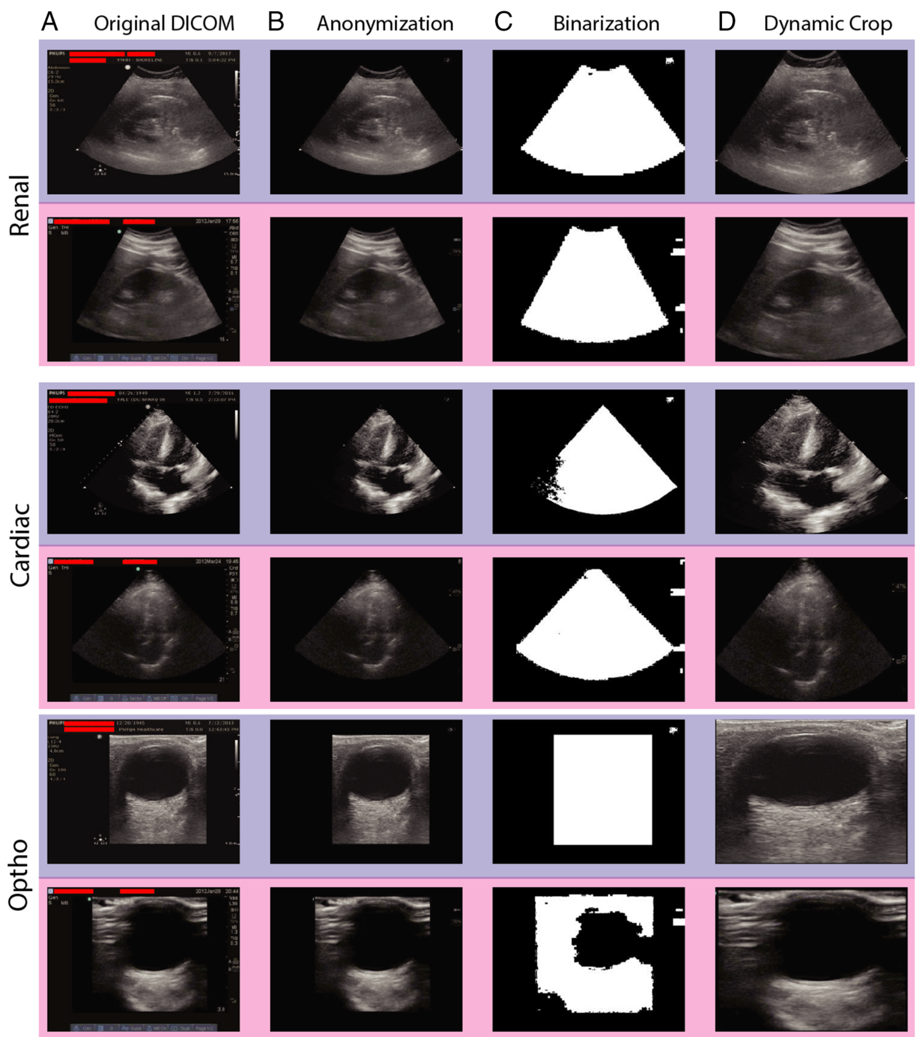


with no processing steps selected. These samples were considered unmodified and used as comparisons for anonymization and cropping. Successful anonymization was defined as complete removal of patient information, including name, date of birth, and medical record number, from all frames. To assess cropping, either a binary threshold value of 1e-07 (estimating 0 but accounting for floating-point calculations) or Otsu's method was used, and the output clips were compared with the negative control. A successful crop was defined as one that included the entirety of the US cone by visual inspection. Inter-reviewer agreement was calculated after reviewing all frames within a video clip using the Cohen κ score in the Python scikit-learn library.[40]

Results

We tested this software on 100 compressed DICOM videos captured during routine clinical care at an academic hospital emergency department and extracted

Figure 3. Ultrasound video-processing pipeline with representative images. Videos from renal, cardiac, and ophthalmologic scans were captured with curvilinear, phased array, and linear transducers, respectively. Ultrasound examinations were performed on instruments from 2 different manufacturers: Philips Healthcare (Bothell, WA; blue boxes) and SonoSite, Inc (Bothell, WA; pink boxes). Images shown were extracted from the first frames of the processed video clips. Red boxes represent redacted patient ePHI.



from a QPath database (Table 1). We observed that 100% of clips were anonymized successfully, deleting ePHI with perfect inter-reviewer agreement ($\kappa = 1$). We also noted that anonymization also removed a number of other image elements, including the manufacturer label, depth markers, and user-entered image labels. For the binary and Otsu thresholding, we observed 96% ($\kappa = 1$) and 14.5% ($\kappa = 0.87$) successful crops, respectively. Given the limited utility of Otsu thresholding, we do not include the technique in the final software package. We then evaluated the 4 clips that failed binary cropping, observing that all were captured by a phased-array transducer on a Philips Sparq machine during cardiac examinations. Two clips were captured in the parasternal long-axis view, and 2 represented the parasternal short-axis view. We subsequently extracted 20 more clips captured during routine clinical care that were evenly divided between these views and analyzed them with this pipeline. Consistent with our earlier results, we observed 100% anonymization ($\kappa = 1$). All 20 clips were correctly cropped by binary thresholding ($\kappa = 1$).

Since our approach leverages an image segmentation step, we then calculated the number of pixels within the calculated US cone that were blanked during the initial anonymization step. For this analysis, we used only videos in the original data set ($n = 96$) that were cropped correctly by the binary threshold method. We found a mean and SD of 0.21% and 0.54% pixels modified, respectively. Only 5 clips had greater than 1% of pixels modified. All 5 clips were lung windows captured with a linear transducer. On manual review, we noted that these images had substantial hypoechoic regions relating to the overlying rib anatomy. We did not observe any cases in which the modification of pixels affected the visual interpretability of the videos. In sum, these data suggest that this anonymization step is specific to fixed image elements such as ePHI and does not substantially affect data contained within the US cone.

Table 1. Summary Counts for US Samples Used in this Study

Category	n
Manufacturer	
Philips	50
SonoSite	50
Transducer	
Linear	37
Curvilinear	25
Transvaginal	20
Phased array	18
Anatomy	
Renal	20
Pelvic	20
Abscess	20
Lung	20
Cardiac	20

Discussion

The US-Pro software enables efficient local US video preprocessing with robust ePHI removal and accurate dynamic cropping. This program enables data export in video or high-performance machine-learning–compatible formats. We anticipate scenarios in which researchers use this pipeline to anonymize US videos to make medical data accessible in-house or to the larger scientific community[27] without sharing PHI.[41] Although the described algorithms were tested on data from varied organ systems captured from different machines and with all major transducer types, individual US clips should be reviewed by experts to ensure that their quality and content are appropriate for downstream analysis. For example, point-of-care US practice sometimes includes the capture of multiple clips of a single anatomic feature with various overlaid elements (e.g., color Doppler). User input will be required to identify those images applicable to the research question at hand. Furthermore, a key limitation of this approach is that it is only compatible with US videos. The use of US stills in this pipeline will require the integration of a separate image-processing platform.[11]

Distribution within the Docker environment greatly facilitates method adoption and reproducibility within the larger community, since all library requirements are bundled within the distribution software.[42] In addition, Docker provides task scalability, as users are able to deploy more system containers as needs emerge. Through integration with a system such as Singularity,[43] this pipeline can be securely deployed in an academic high-performance computing cluster, enabling manipulation of large data sets within a local system. We anticipate that the US-Pro application will serve as a model for future collaborative scientific computing efforts.

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