AD______________

AWARD NUMBER: CDMRPL-16-0-DM167028

TITLE: The Burn Medical Assistant: Developing Machine Learning Algorithms to Aid in the Estimation of Burn Wound Size (BURNMAN)

PRINCIPAL INVESTIGATORS: Maria L. Serio-Melvin

PERFORMING ORGANIZATION: USAISR

REPORT DATE: January 2020

TYPE OF REPORT: Final

PREPARED FOR: U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
Jan 2020	Final	10/01/2016 - 09/30/2019

4. TITLE AND SUBTITLE

The Burn Medical Assistant: Developing Machine Learning Algorithms to Aid in the Estimation of Burn Wound Size (BURNMAN)

5a. CONTRACT NUMBER

5b. GRANT NUMBER CDMRPL-16-0-DM167028

5c. PROGRAM ELEMENT NUMBER

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

6. AUTHOR(S)

Maria L. Serio-Melvin

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

U.S. Army Institute of Surgical Research (USAISR)

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for Public Release; Distribution Unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The American Burn Association reports that roughly 450,000 patients receive hospital and emergency room treatment for burns each year, and of these patients, roughly 3,400 burn injury deaths occur. According to the Centers for Disease Control and Prevention (CDC), burns and fires are the third leading cause of death in the home. Thermal injuries occur in approximately 10% of combat trauma. Mortality rates for these patients remains high, half of casualties with 60-70% Total Body Surface Area (TBSA) burns die, whereas in civilian centers, roughly 50% of similarly matched patients with an 80% TBSA die. Since battlefield resources are inherently limited, triage is essential to determining the appropriate resources to be applied, and this is especially relevant to thermal injuries. It is critical for the medic on the battlefield to be able to make a rapid, accurate assessment of burn severity for triage, resuscitation, and evacuation planning purposes. But an error on the battlefield in estimating burn severity of over 10% can result in medics spending resources on unrecoverable patients at the expense of recoverable patients, or providing expectant care to a patient who could otherwise be saved.

15. SUBJECT TERMS-

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
U	U	U	UU		USAMRMC
					19b. TELEPHONE NUMBER *(include area code)*

TABLE OF CONTENTS

1. INTRODUCTION:

Previous studies have shown that pre-hospital care is critical for avoiding complications and improving outcomes of combat casualties. For the current conflicts, burn injuries occur in approximately 10% of combat casualties. Morbidity and mortality associated with thermal injuries is closely associated with the effectiveness of resuscitation within the first 24-48 hours. Therefore, it is critical for care providers to make rapid, accurate assessment of a patient's TBSA burned for triage, resuscitation, and evacuation planning purposes. Unfortunately, inexperienced providers often over and under estimate burn wound size and consequently institute less than optimal resuscitation.

There are no current technologies available that automate TBSA and burn depth assessment or annotation. There are several burn drawing applications that estimate TBSA using 2D and 3D models, but they require manual and subjective human interaction. In order to fully automate this process we analyzed data from multiple visible and IR band images of the patient using commercial off the shelf (COTS) cameras. We developed an **e**nhanced **L**und and **B**rowder (eLB) system that maps these images to a full body representation that reflects the actual patient morphology. We have evaluated several methodologies to address the challenge of automated mapping of images to the body and TBSA calculation. Once we validated the mapping methodology, we applied machine learning (ML) algorithms to estimate the percent TBSA and approximate burn depth from the combination of source imagery. We have delivered a software package that automatically analyzes burn patient image data, maps the images onto a 2D eLB, allows experts to annotate or change annotations and calculates the %TBSA of the patient.

2. KEYWORDS:

Burn, artificial intelligence. machine learning, machine vision, image annotation, training, and validation

3. ACCOMPLISHMENTS:

What were the major goals of the project?

Objective 1: Place images of human subjects onto a standard anatomic diagram of the human body and create a multi-spectral image database of burn wounds for ML. (Months 1-16)

- 1.1 Applied Research Associates (ARA) will provide an advanced imaging platform for researchers at the United States Army Institute of Surgical Research (USAISR.) (Month 5)
- 1.2 USAISR and ARA will create de-identified database of enhanced burn wound diagrams. (Months 1-16)
  - 1.2.1 USAISR submits and obtains IRB and IACUC approvals.
  - 1.2.2 USAISR images healthy volunteers, burns on a porcine burn model, and patients admitted to the burn center.
  - 1.2.3 Software engineers at the USAISR, ARA, and OSU create enhanced burn wound diagrams.
  - 1.2.4 USAISR sends de-identified imaging data to ARA and OSU for preprocessing.

Major Milestones:

- USAISR to write a human subject research protocol (taking admission photos of burn patients admitted to USAISR using our developed technology) approved by USAMRMC HRPO (Month 4)
- Enhanced burn wound diagrams created and processed (Month 16)

Objective 2: ARA to train machine learning software to model raw images of burn wounds. (Months 5-19)

2.1 USAISR to provide expert annotation of enhanced burn wound diagrams within the de-identified data set. (Months 5-16)

2.1.1 Ohio State University (OSU) uses enhanced burn wound diagrams and their existing software to trace wounds and estimate of % TBSA.

2.1.2 Experts in burn wound care at USAISR estimate wound size and burn depth; review OSU's enhanced burn wound diagrams to confirm or correct these estimates as needed.

2.1.3 USAISR sends expert annotations to the de-identified enhanced dataset to ARA.

2.2 Create a machine learning model. (Months 5-19)

2.2.1 ARA uses training data set to create ML algorithms to automatically estimate burn wound depth and %TBSA.

2.2.2 ARA uses the evaluation cohort to demonstrate the ML algorithm reaching within 5% of expert's judgment.

Major Milestones:

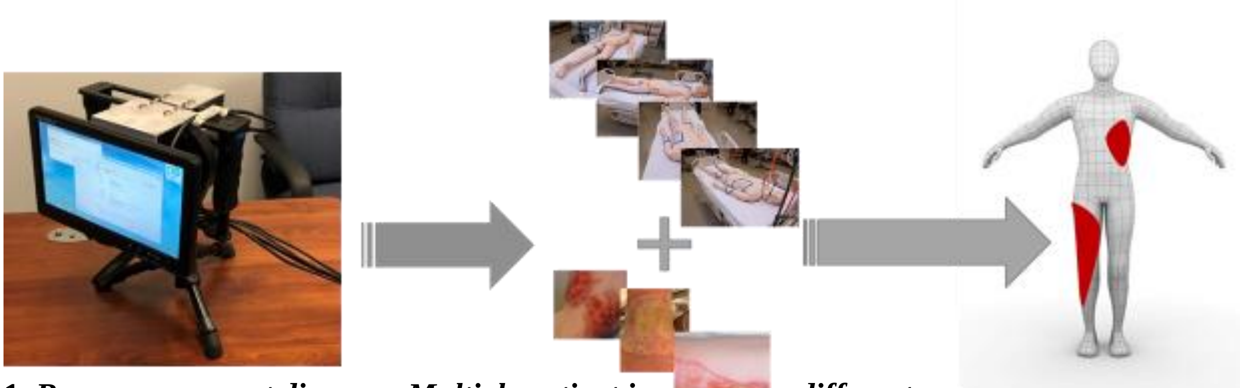
- Two sets of expert annotations for each image. (Month 16)
- Machine learning model. (Month 19)

What was accomplished under these goals?

USAISR currently has BURNMAN hardware and software which consists of 1) An iPad Mini with the Structure Sensor and pose template software, 2) the BURNMAN laptop (server) that contains the BURNMAN machine learning algorithm. We can demonstrate how to take a photo of a person w/ the BURNMAN iPad Mini using the pose templates, and show how the BURNMAN ML software takes all of the photos, segments skin from the background and composes an Enhanced Lund and Browder (eLB) diagram. The eLB shows the visual photos taken of the person "stitched" together, forming a diagram (basically) in the shape of that person. The software can also automatically calculate the TBSA burned, showing a table of the percent partial and full thickness burns. The eLB is automatically labeled with categories ranging from normal skin to 4th degree burned and also allows for clinicians to edit the labels. The technical readiness level is ~4-5. Each of the described features need to be improved because the ML algorithm was built on a very limited data set.

Major Activities:

1. Imaging hardware design
2. Development of clinical imaging procedure
3. Retrospective data collection of historic burn patient admission photos. (Patients were alive when photos taken, then died during their hospital stay.)
4. Prospective data collection using volunteer subjects
5. Prospective data collection using animal subjects
6. Automated Burn Recognition Algorithm
7. Development of the enhanced Lund & Browder Chart
8. Development of burn wound image annotation process
9. Development of an automated process for generating an eLB



1. ***Burnman concept diagram. Multiple patient images from different angles will be combined with localized multi-spectral burn images to create a 2D Lund and Browder Diagram.***

To accomplish our final objective, a number of interim steps were necessary. Some of these steps were correctly forecast in our initial research plan, others did not come to light until we began to implement our approach in a realistic clinical environment.

Step 1 Clinical Data Collection: During the admission process, a clinician will photograph the patient's wounds. Today, a standard Red, Green Blue (RGB) visual, digital camera is used and this process is mostly ad-hoc depending what the clinician believes will be relevant for clinical care. This often results in photos that require significant cognitive load to transfer to an anatomical diagram. During this research, we discovered that, even in an advanced ICU care facility, it was not feasible to pose patients in a way that matched anatomical diagrams, and thus directly using a single image was not possible. To address this issue the BURNMAN team developed a set of standardized patient pose templates that were clinically reasonable and also ensured coverage of the entire anterior and posterior body surface. We further developed software that assisted clinicians in posing and positioning the camera for optimal data collection.

Step 2 Image Processing to Remove Background: To create a clear eLB, we must separate the foreground (pixels that represent the patient's body), objects that clutter the scene (i.e. intravenous fluid tubing, EKG pads) and the background (pixels representing the room, equipment, or other things in the room behind the patient). This process can be automated using off-the-shelf algorithms when the foreground and background are visually very distinct (e.g., chroma-key on green-screen backgrounds). However, in a clinical setting (and even more so in a pre-clinical setting) these images have significant clutter and color overlap. Additionally real-world lighting, diverse skin-tone, and wound differences complicated this task. The BURNMAN team was able to develop machine-learning-based image processing tool that automatically extracts (aka segments) patient foreground from environmental background, including clutter objects in the scene.

Step 3: Detection of Burned and Unburned Skin: Our initial plan was to use thermal or multi-spectral images to determine the depth of burn. Successful applications of this technology to this problem have been published, and we intended to train a machine learning model to perform this task. However, the team also recognized that specialized equipment (like a multi-speckle imaging camera) might not be practical for pre-hospital care scenarios. Therefore, the BURNMAN team developed an MSI-based camera platform and tested image capture with porcine burn models, via an amendment to a current animal protocol. We also used this MSI camera platform to take photos of consented human volunteers. We discovered several issues, including that using the larger/heavy equipment was not practical for human-patient use, subjects had to be held still for too long because the camera was slow, and that that proper control and augmenting of scene lighting was critical to success. Also, the MSI camera platform was heavy (approximately 20 pounds) and therefore very difficult to aim and hold still without shaking for the length of time it took to take photos through all of the MSI filters. Therefore, we determined that further work on an MSI-based approach would not be profitable for key objectives. To this end, our OSU teammate developed a web-based tool (called Label Coach) for allowing USAISR Burn Center subject matter experts (SMEs) to annotate burns graphically from standard RGB photographs, and we began collecting SME labels for a set of USAISR's historic burn patient images. Using this data, the BURNMAN team developed ML models that differentiated skin, tattoos, and burns. Because we were unable to collect data on posed burned patients in the current period of performance, and we were only able to label a small subset of historic burn patients (unposed images) we have a partial solution (technically two promising but partial solutions) that we anticipate will improve with additional data. These are integrated with foreground segmentation (step 2) so that we can include segments for clothing, bandages, tattoos, and other non-skin classifications into a model of the patient morphology (and thus be counted in the surface area calculations).

Step 4: Mapping Images/Burn Labels to an Enhanced Lund&Browder (eLB) diagram: Our plan for creating the eLB was initially based on extracting the foreground from a single anterior and posterior image – when taking such pictures proved clinically infeasible, we changed our plan to assembling multiple posed images into the eLB. This is similar to photogrammetry approaches, with the critical differences that both patients and camera are moved between images (both intentionally and not). The BURNMAN team was able to develop a machine-learning-based solution that recognized body landmarks in images, and used these landmarks and image overlap to produce a set of homographies, the mathematical transformations that relate images to each other. In combination background and body segmentations results, these homographies enable us to assemble a full body image (anterior and posterior) from a set of posed images.

Step 5 Burn Labeling and %TBSA calculation: We developed additional software that presented the eLB (with all background removed) in multiple forms: image (photo content), label (colors representing annotation), and hybrid (translucent color annotations over photo content). From the eLB, we were able to calculate the %TBSA as well as %'s for each annotation class (e.g., 10% of the surface has a full thickness burn). We recognized that clinicians would need the ability to correct/change the automated assessments. We developed software that allowed an SME to change the automated labels or manually label the original images, and automatically apply these changes to the eLB. This approach allows the system to be used while we continue to collect and label additional training data that will improve burn classification.

Figure 1, shows the planned development process for the 2 years of BURNMAN research. In reality, many of the steps required multiple iterations and the IRB process took long (and methods changed based on lessons learned and advancements in the technology). In reality, this research effort frequently discovered new challenges at each step (often reflecting how technologies might not readily translate from the literature or lab environments to realistic clinical or pre-hospital scenarios). It often required the team to learn from issues, reorient, change our approach, and press forward. In the following sections we outline all of our efforts, including those learning experiences that helped formulate our team's final approach.

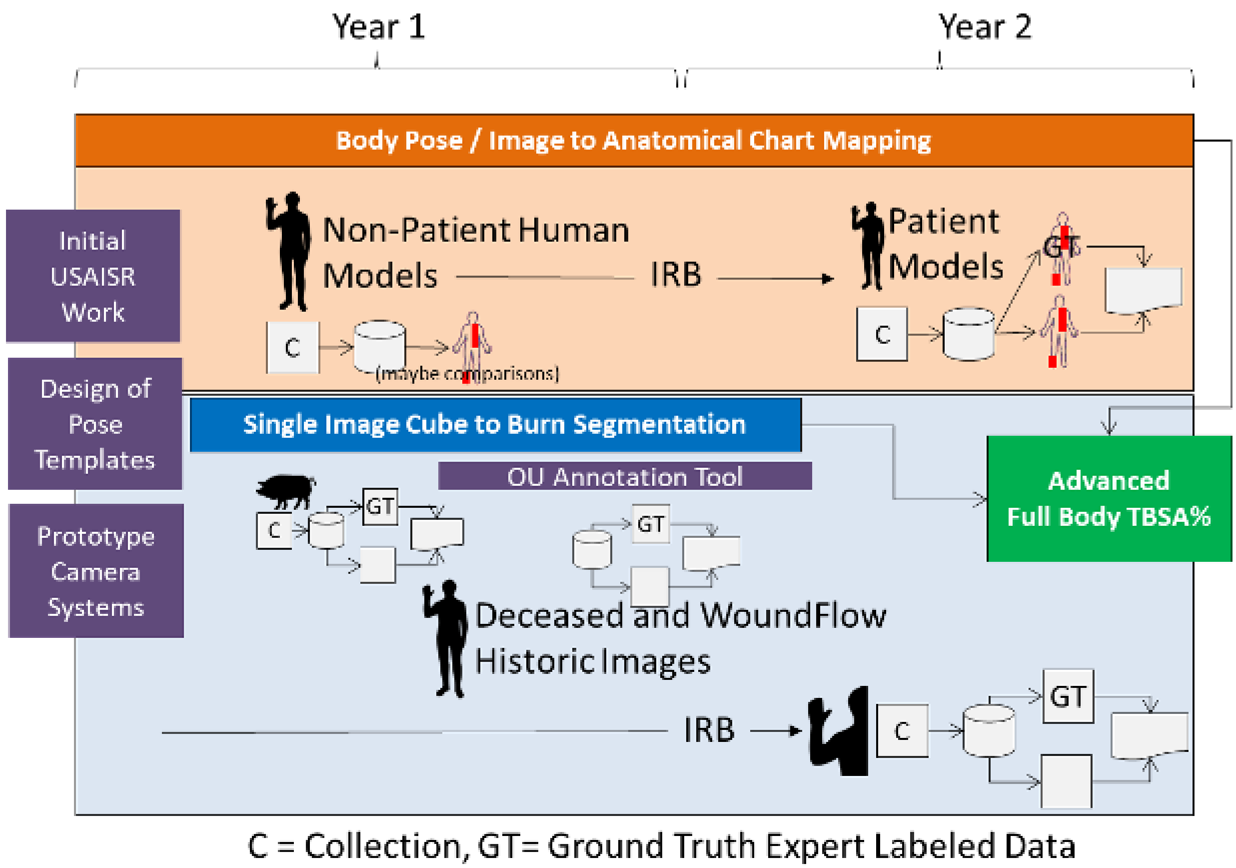


Figure 2. ***Burnman Project Plan. As a result of technical and administrative delays for capturing prospective burn patient images, we have adjusted our approach to take advantage of available historical data and animal image data.***

1. Imaging hardware design

a. Multi-Spectral Imaging System

After a thorough review of the project requirements and the current technical status of the RVS Pixnet camera system, we determined that the Pixnet was not suitable for use in the project. As such, RVS was dropped from the team and an alternate off the shelf camera solution was identified. The SpectroCam VIS-NIR 5MPixel camera system was selected based on a thorough market survey of current Commercial Off the Shelf (COTS) technology and after review of the technology offered by RVS (Figure 3). This system offers the necessary resolution, flexibility, and spectral bands to support the research objectives.

Figure 3. ***SpectroCam VIS-NIR Camera.***

The project team reviewed several means of mounting the camera system to enable consistent images to be taken by an individual. A mounting system was acquired for the cameras which attached to a standard Computer on Wheels (COW) cart in the Burn Center, but after testing in the Burn Center, we determined that this mounting method was too unwieldly to be used in data capture. We elected to acquire a hand-held mount to hold the MSI camera and other supporting hardware. We also acquired a new lens for the MSI camera to increase the field of view, enabling fewer pictures of the patient to capture the full body. Ideally, we would be able to acquire 100% body coverage of the front of the patient in prone position with no more than 3 photos, with additional photos to capture the rear, sides, and tops of the feet as necessary.

The primary system is designed around the Multi-Spectral Imaging (MSI) camera that collects 8 Visible Near Infrared (VNIR) bands. This platform requires additional support equipment, such as a laptop. We integrated an Intel Real Sense depth imager, a touch screen, and a custom application for pose management and multi-camera automation. Where previously it required two people, multiple computers, and considerable expertise to collect data – it is now a one person, one laptop, and simple interface (*Figure 4*).

Figure 4. Our MSI platform combines a COTS MSI imager (large lens), Intel RealSense Depth camera (blue bar on front), and a touchscreen (left picture) into a portable device. This platform is tethered to a laptop that is required during data collection, but imaging is controlled via the integrated touchscreen and a custom Windows-based application.

Ultimately, we determined that the size, weight, and time requirements of using this MSI imager was not practical for collecting data in an active Burn ICU, and that controlling the lighting was unlikely to be tolerated during patient care or pre-hospital (outside) scenarios.

b. iPad-based Imaging Systems

We evaluated other RGB and Depth sensor systems with the goal of generating a large number of images suitable for use in an *eLB* where the MSI camera was not feasible for use. The systems we (USASR) evaluated include: Microsoft Kinect, FLIR One, Hero 7 GoPro (GoPro, Inc.), Intel® RealSense™ ZR300-Series, iPad (Apple), Galaxy (Samsung), Structure (Occiptal) and Intel Euclid. This process took approximately 12 months.

To support volunteer image data collection and to assess the use of depth map data, we (USAISR and ARA) developed a version with just RGB and depth image data using an iPAD Mini. This small and light-weight platform collects color and depth data. It was designed around an iPad Mini so as to be easy for clinicians to use today as a direct replacement to a traditional digital camera. The ability to capture depth data (using an integrated Structure sensor) and control via our custom app for pose management made this a powerful data collection tool that was inexpensive and quickly clinic ready (*Figure 5*).

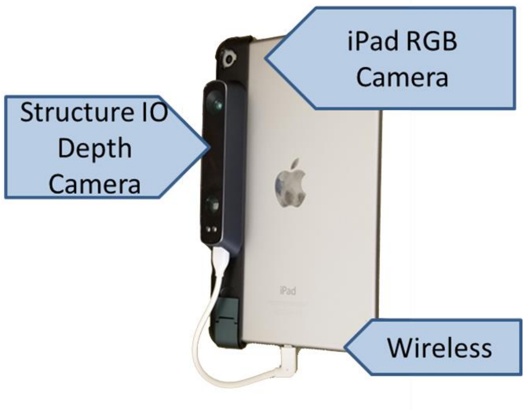


Figure 5. Our Mini platform includes an iPAD Mini with Structure Sensor. A custom iOS app helps clinicians setup the correct poses and take matched color and depth images. All of the required components for data collection are shown above.

This combination enabled us to investigate what is feasible with various collection systems and levels of data. Our objective was to determine the minimal required hardware to achieve the target TBSA accuracy.

ARA enhanced the iOS app based on initial clinician feedback from USAISR and completed the MSI camera application software.

c. Image Processing (ARA lead with USAISR assistance)

The first major challenge in this process was to extract the image of the patient from the background clutter in the image. This included things both behind (e.g., walls, floors) and in front of the patient's skin (e.g., sensors, sheets, bandages, cloths). These must be removed or segmented from the image to generate the correct outline and surface area of the skin. We called this process "skin segmentation" and it was significantly complicated by various colors of skin, hair, shadows, and burns themselves. We had attempted this using several image processing techniques with mixed and inconsistent results due to lighting changes and color variation in environment. We incorporated depth information in the collection process, which provided additional data to enable image segmentation.

USAISR Also explored the FLIR One thermal imaging camera. Our hypothesis was that the thermal image did not depend on the environment, so shadows as well as other objects within the camera view, should not affect the outcome of obtaining the body silhouette. Both luminescence and thresholding using the hue and saturation value (HSV) were used to attempt to isolate the patient from the rest of the image. This should have provided not only the silhouette of the patient, but also the mask that could be used for overlaying the actual RGB photo of the patient with the *eLB*. Unfortunately, thresholding with a thermal image could not entirely isolate the patient from the rest of the image. Anything that had a heat map/signature similar to the person in the photo was included in the photo, such as another person or a computer monitor (Figure 6). We also found that loose fitting, rolled/bunched up clothes or a military uniform blocked the heat signature.

Figure 6. FLIR One Composite of thermal image mask and RGB image (left) and FLIR One Thermal Image (right).

In Figure 6, the ambient air around the patient diminished the silhouette, making it difficult to see between the fingers. Although this method proved that using the FLIR One thermal imager worked better than other methods (i.e. Chroma key, edge detection,) it was not reliable enough to use for creating the *eLB*. We also tried using the Convex Hull algorithm from the OpenCV library with the Canny edge detection with worse results. The Convex Hull algorithm tried to close edges or contours to form a complete closed contour which would give a complete body silhouette. Unfortunately, the Convex Hull algorithm was adding lines from two completely different contours and resulted in an unrecognizable image.

Ultimately, ARA was successful in skin segmentation through the application of machine learning techniques. They segmented the skin through a neural network using an auto-encoding technique. The original image was encoded through the neural network to develop a low-resolution latent representation of the image. During unsupervised training, the decoding side of the network reconstructed the image. After initial training, they replaced the decoding neural network with one designed for segmenting and training in a semi-supervised manner using a set of manually labeled outlines. Finally, the original image was then run through both the encoding and decoding neural networks to produce a segmented image, removing everything not identified as skin. This process is shown in ***Figure 7***. This is less sensitive to color, lighting, and clutter issues that are precedent in admission photos.

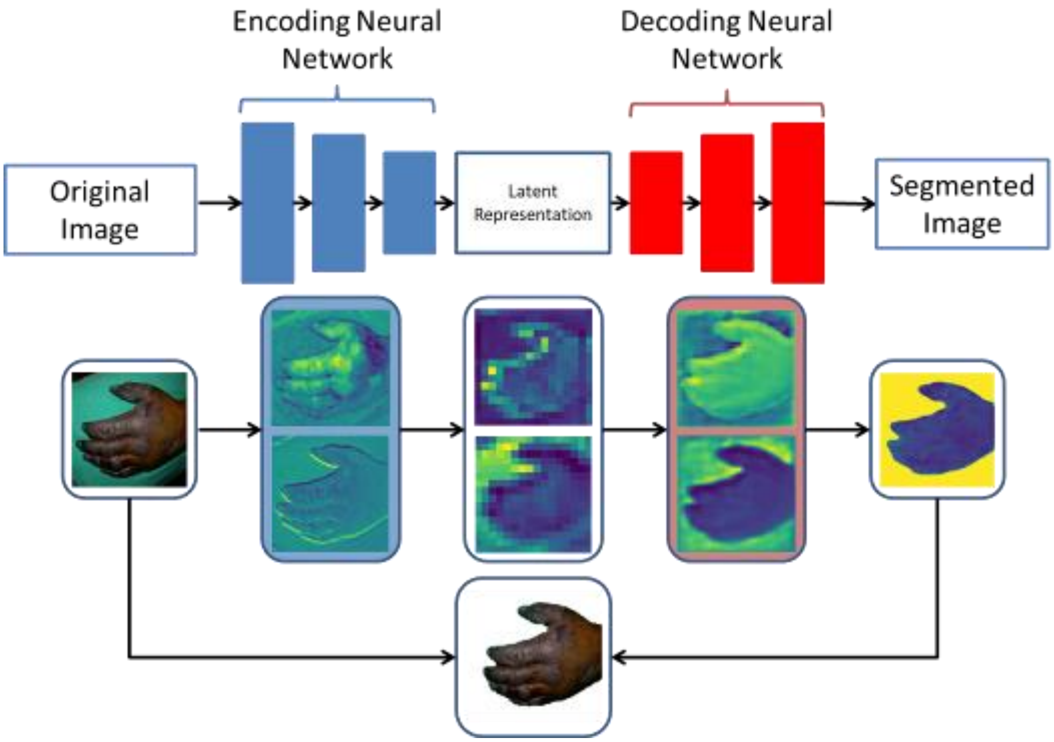


Figure 7. Our auto-encoding neural network (ANN) for skin segmentation using an auto-encoding network and semi-supervised training approach to accurately segment skin.

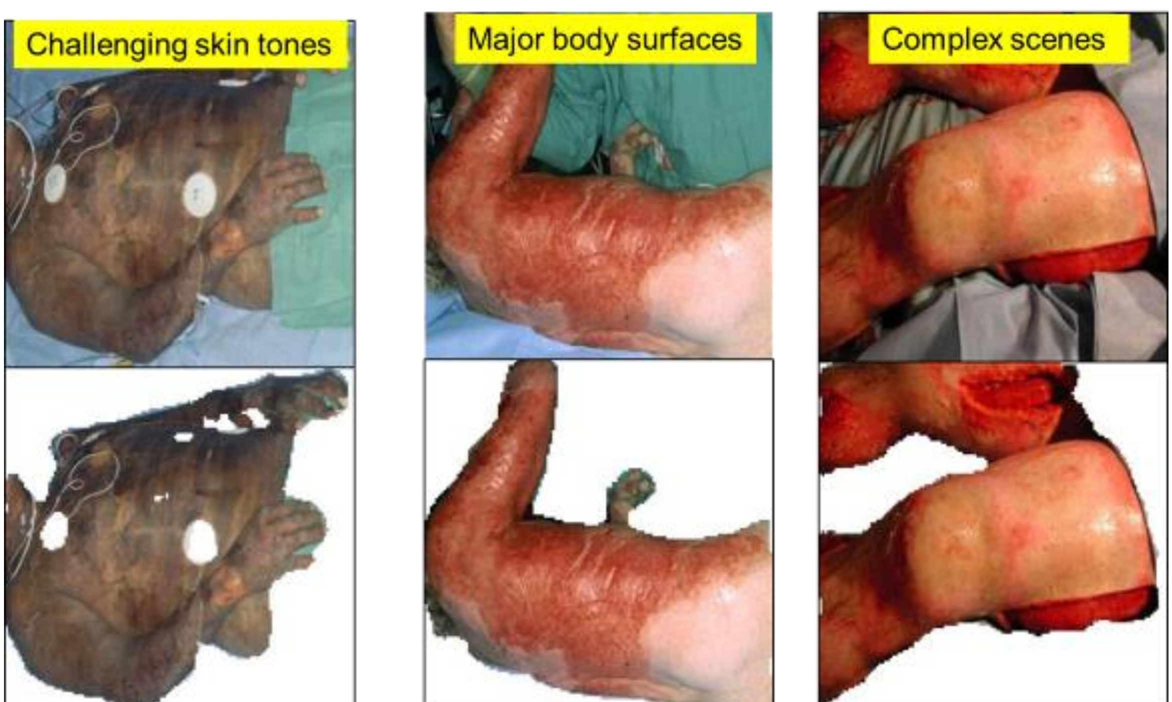


Figure 8. Segmenting skin from background. Our ANN-based machine learning algorithm is semi-supervised. This means that it was trained based on many raw/unannotated images and some specifically labeled examples. In these images you can see how our model performs with challenging cases of real burn patients.

ARA successfully tested this process on the historical burn photos from the USAISR dataset and the non-patient human volunteer photos from our own data collection. As shown in ***Figure 9*** and ***Figure 10***, the results are very positive. Cases where the system removes features such as the clinician's hands and arms are enabled because the training set (for the semi-supervised aspect) included cases where similar "clutter" was labelled as background.

Figure 9. Historical burn patient data set.

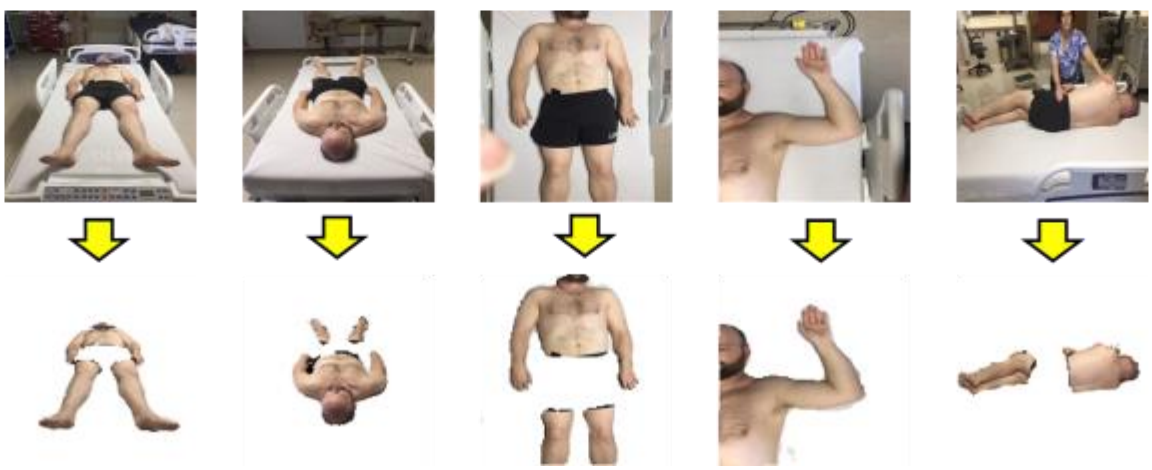


Figure 10. ARA image segmentation process acts as a "skin detector" for images by removing image content that does not appear to be patient skin. Notice, this includes background (e.g., desk) and foreground (e.g., shorts) content. Our novel ANN-based approach is also able to differentiate non-patients (e.g., the nurse) in some cases

Since patient skin color, ambient light, and scene complexity can all negatively affect the performance of computer vision techniques, ARA developed their approach using training data that included these challenging situations. Our training set included about 900 historical photos. About 90% of the images we used to train come from historical patient records that had not been annotated by experts. 10% of the images were annotated to designate skin. Our Semi-Supervised ANN-based approach was able extrapolate the feature characterizations of skin to the entire data set. While initial results were good, they can improve upon them simply by providing additional data (both unannotated and SME annotated). If more images with wider ranges of skin tones and scene complexities are obtained, the algorithm would do better recognizing them. We do not know the upper limits of this approach at this time, but believe that the current results will be sufficient for the next steps of this research.

These segmentation results can be used to pre-filter data prior to more detailed burn characterization and for body localization algorithms (to determine how to map the skin in the image to a 2D or 3D patient model).

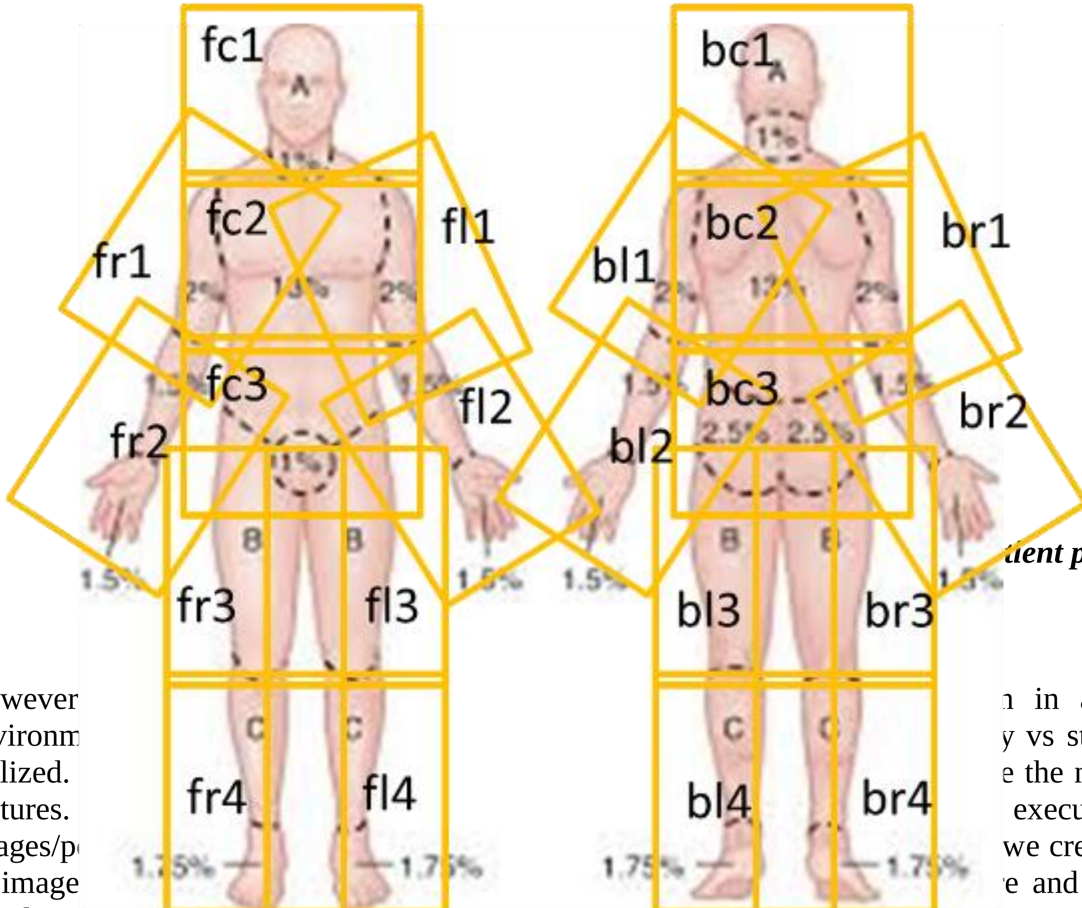
2. Development of clinical imaging procedure

ARA, with USAISR's input, developed custom software using the vendor's software development kit (SDK) to streamline the process of taking images. This depended on a consistent protocol for capturing images to ensure maximum coverage of the patient. With training, the algorithm will be able to identify body regions regardless of pose, but for initial data capture, it was important that images be consistent, across subjects.

Currently, burn admission photos are taken after hydrotherapy (shower/bed bath) debridement. Photographs are only taken of burned body parts. If unburned sensitive areas such as genitalia and female breasts must be in a photo, the areas are covered with a towel. Patients with smaller burns may have non-burned body parts covered. Photos are ideally taken in a systematic fashion, such as around the body in a clock-wise or counter-clockwise fashion, taking an anterior photo of the extremity, then the posterior photo. Photos of the hands are taken with the upper extremities and photos of feet are taken with lower extremities. On rare occasions, seemingly severely burnt hands and/or feet may require separate photos to be taken.

The order of photographs for each subject and each session can vary greatly depending on location of burn, flexibility of the patient, cleansing of the wounds, and application of dressings and how well the patient tolerates burn care, such as being turned side to side. Most commonly, the patient is in a patient room, lying on blue sterile sheets on a bed; this happens with reasonable regularity. Ideally, blue or green surgical towels are used as a background for the photos, such as when an extremity is lifted to photograph the posterior; however, this happens with much less frequency.

Based on the current standard operating procedure of taking photos of burn patients on admission to the USAISR Burn ICU, we established a chart for template photos identified by body region. The initial version of the chart (***Figure 11***) included a total of 22 separate photos.



...ient photos.

However ... n in a clinical environm... y vs stand were realized. ... e the number of pictures. ... executing the images/p... we created a set of image ... e and to which people could easily align images to achieve consistency. As a result of these advancements, we have reduced the number of photos of the templates from 22 to ~13. Some are shown in ***Figure 12***.

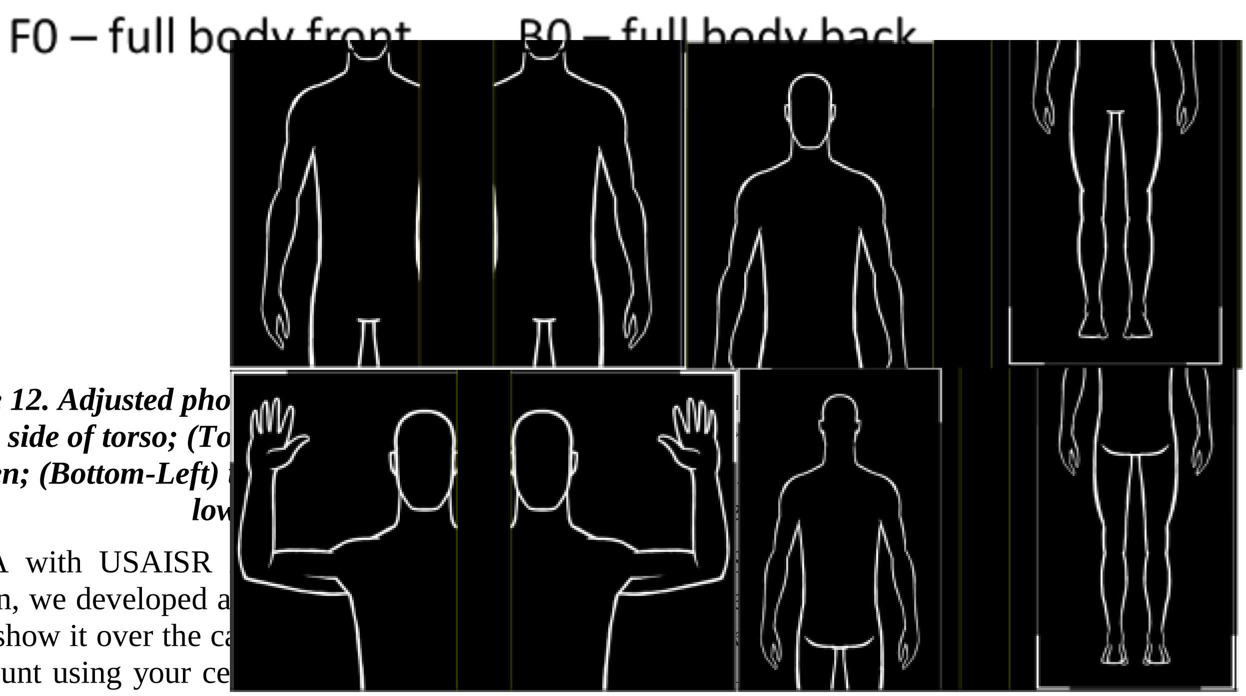


Figure 12. Adjusted pho... opposite side of torso; (To... abdomen; (Bottom-Left) ... low...

We (ARA with USAISR ... application, we developed a... the pose, show it over the ca... bank account using your ce... swipe away sections without burns and focus the burned body part within the correct outline (as shown in ***Figure 13***) to take the photos. This will ensure the photos are properly registered for the computer. We focused getting images that are clinically reasonable (e.g., minimized discomfort) and provide sufficient data for image stitching, and provide views of a complete patient anterior and posterior.

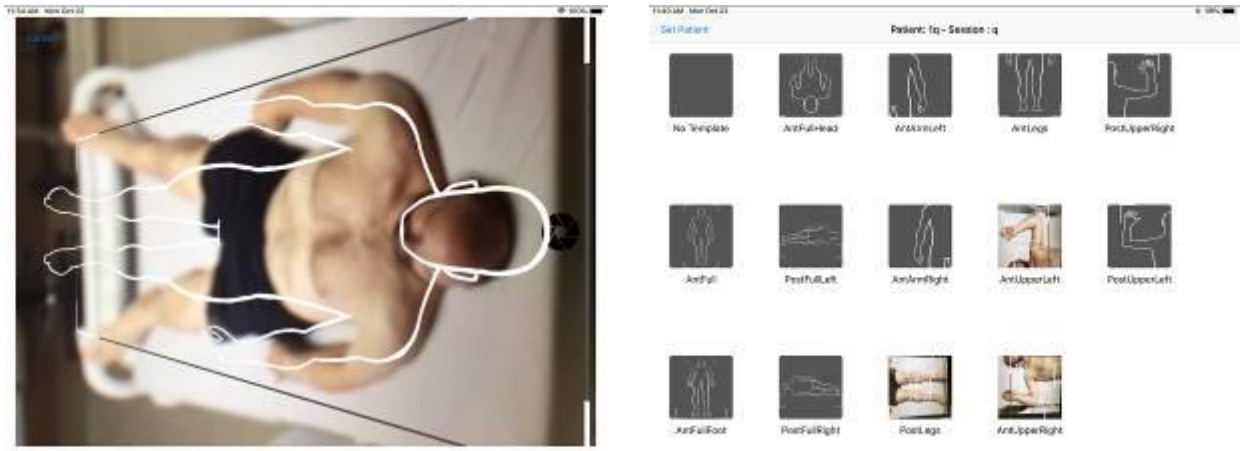


Figure 13. Initial version of the iOS Template Application Screen. Left – screen capture of template applied to live camera view finder for consistent alignment. Right – screen capture of menu for selecting template poses and reviewing previously taken images.

After several months of use, we identified and implemented a number of improvements to the BURNMAN application for image collection. The application is used for both the iPAD Mini with the Structure sensor and the MSI Camera systems.

We originally disabled automatic camera rotation, however, after some data collection, doing this resulted in too much variety in images and lost data. Instead, we identified the optimal aspect for each template and stuck to that aspect going forward.

Additional minor cleanup of the user interface included adding a color Cancel and Take button to the screen (***Figure 14***).

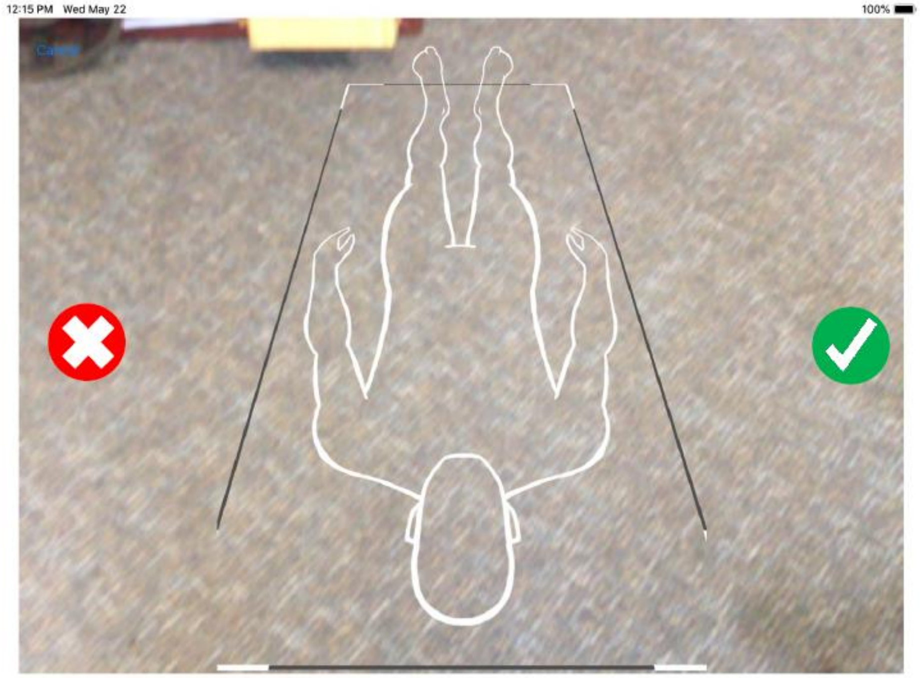


Figure 14. Added a color button for Cancel (red circle with X) and Take (green circle with check).

We enabled an automatic check for Internet access. If the user did not have Internet access, the app will prompt to turn it on. If access is not available, it will enable saving on the device for later uploading, and gray out screens that require downloaded data. If Internet access is available, it will verify that the device can connect to the BURNMAN server. The BURNMAN server is a laptop computer with its own WiFi.

We added a prompt to ensure that preferences are set by the user. Additional preferences and settings include the server (IP or domain name), user ID and password. The settings will automatically verify server access and username and password.

We added a new Introduction Page (***Figure 15***). The system will now enable the user to pull a list of patients in the system from the server, allow selection of an existing patient to add to their record in addition to starting a new patient, require completion of patient ID before proceeding, and select previous patient if ID is entered into new patient field.

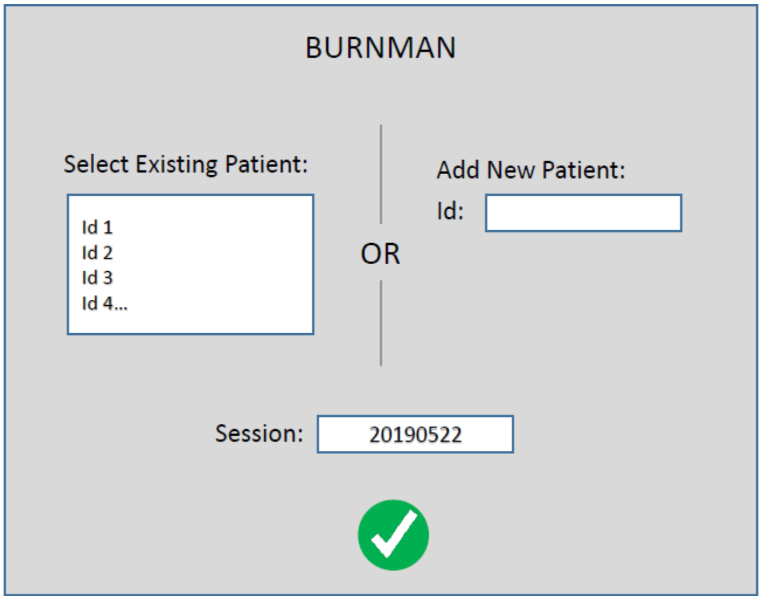


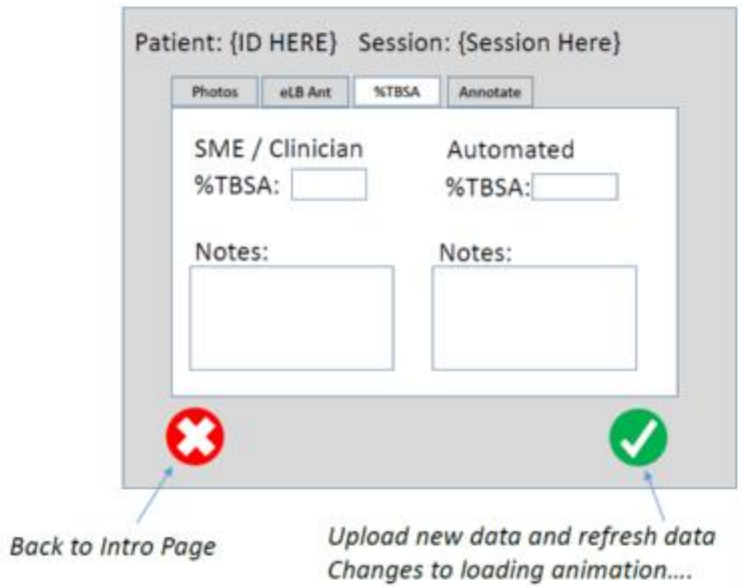
Figure 15. New Introduction page.

We also made adjustments to the main patient dialog screen. The system will download the current eLB from the server, both anterior and posterior. These will be refreshed when new images get uploaded to the server. Minor changes to the templates were also made to improve overlap for image registration. See Figure 16.

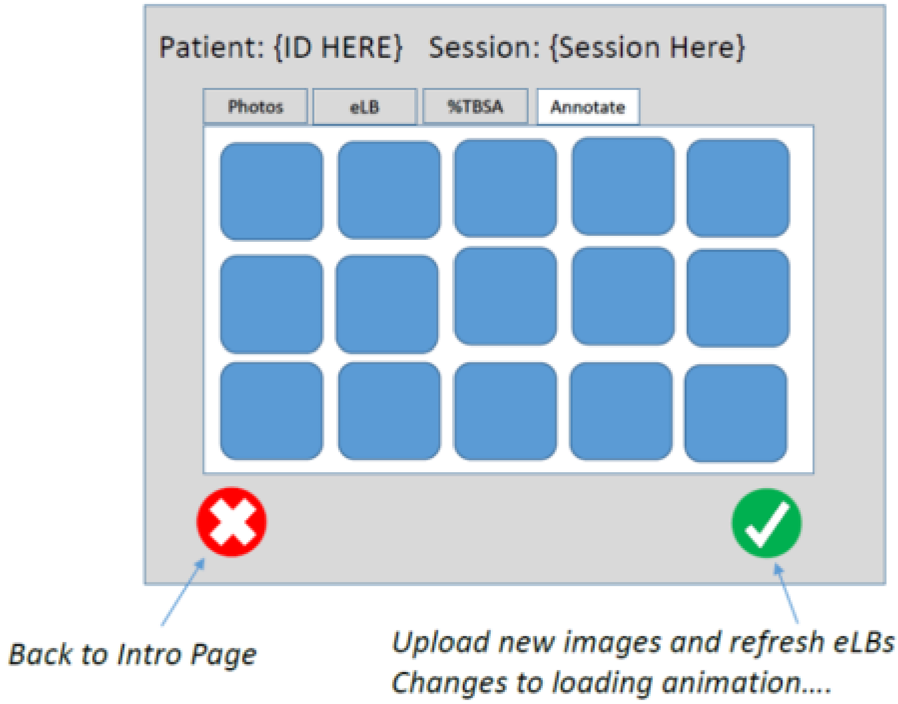
Fi

We added a new eLB tab to enable a user to see the eLB during the image collection process. This tab will load eLB information, and an anterior and posterior image from the server. Clicking or touching a specific body region will pull up the original photos used to generate the eLB for that region. See Figure 17.

We added a new %TBSA Tab. This will display the automated %TBSA calculation based on the available server data as well as the clinician notes on %TBSA. The clinician side is read and write and all notes will be saved to the server. See Figure 18.



Lastly, we added a tab to enable annotation of the photos from within the BURNMAN app. Once photos are uploaded to the server, they will be accessible through the Label Coach annotation tool. Clicking on an image will load the browser to the Label Coach to enable annotating that image. See Figure 19.



3. Data collection using volunteer subjects (USAISR lead)

USAISR applied for and received approval to use non-patient human volunteers for data collection. We tested our equipment with project staff for body recognition. This gave us data for continuing to develop the image-analysis software for the Enhanced Lund-Browder (eLB) charts (

Figure 20).

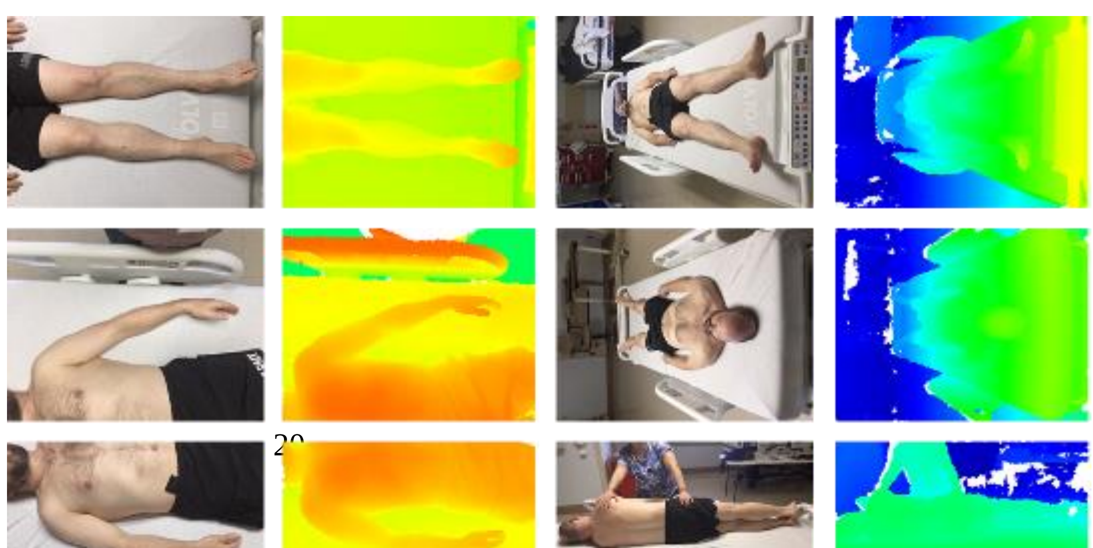


Figure 20. Sample volunteer "patient" photos using our Mini platform. The images shown include six of our pose template images. On the right of each standard color image is a colorized depth image showing the corresponding 3D data collected by the platform.

The USAISR research team collected 1507 photos of 47 healthy volunteers. These photos were taken with the iPad-based camera system, include color and depth data, and correspond to the BURNMAN-developed Pose templates. We (ARA) used this data to train ML algorithms that identify body parts and map images to a patient diagram. This is a critical step towards the enhanced Lund and Browder diagram.

4. **Data collection using animal subjects (USAISR Lead)**

Using porcine subjects, USAISR collected data of known burn patterns using our MSI imaging systems. This gave ARA data for continuing to develop the burn depth detection analytic software that was used in combination with the Enhanced Lund-Browder (eLB) charts to assess TBSA (***Figure 21-Figure 23***).

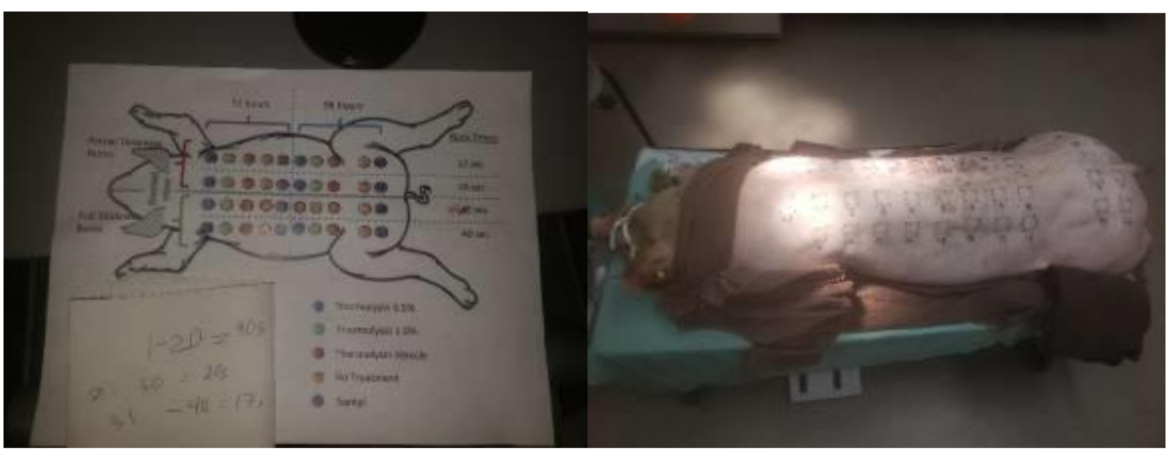


Figure 21. Porcine burn studies provide a number of controlled burns on a single subject, including unburned control areas.

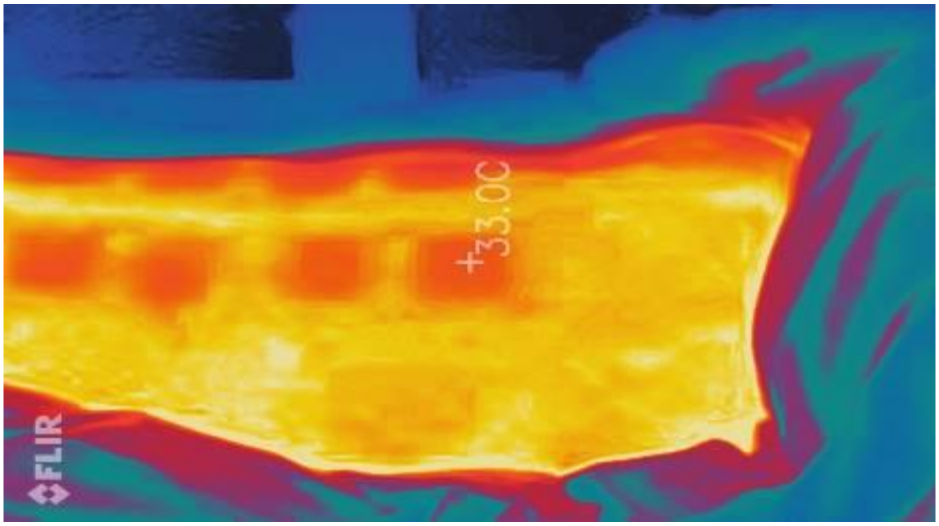


Figure 22. FLIROne image data from a porcine test subject.

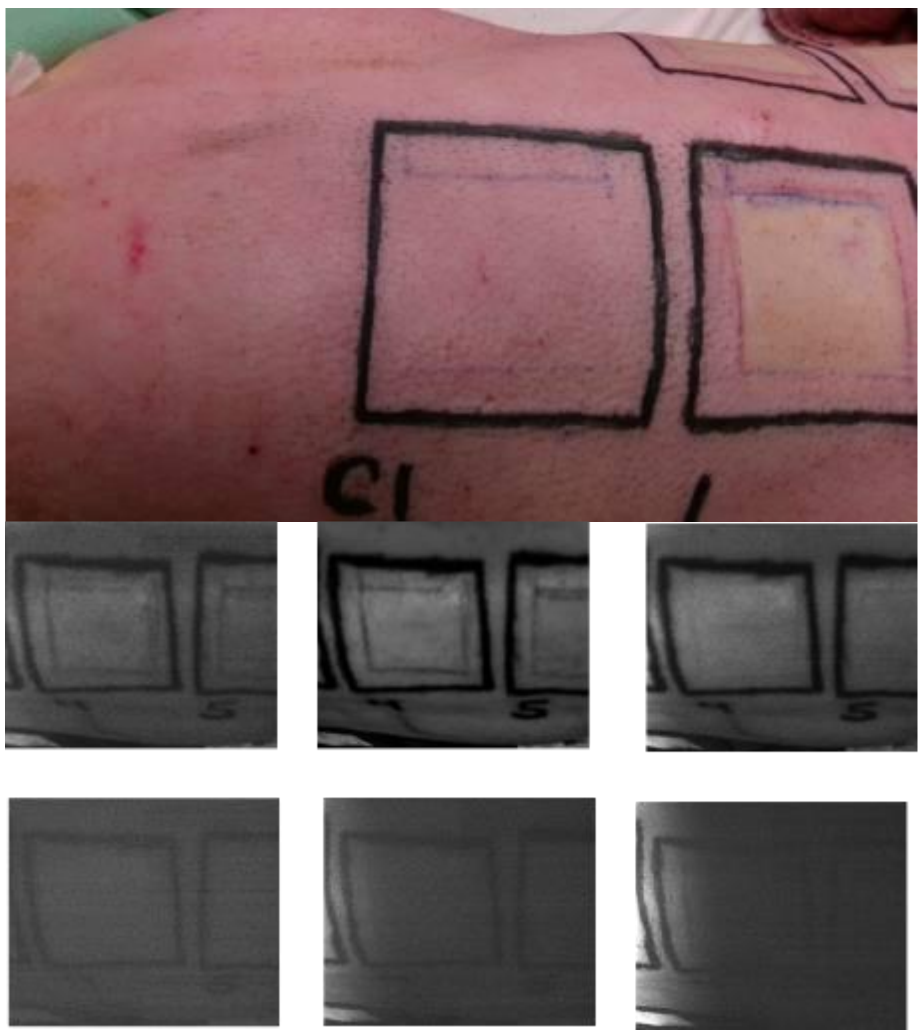


Figure 23. Sample images over multiple bands using our MSI platform. The images show a color/RGB (top) and 6 examples of narrow VNIR bands. Notice that due to the closeness that these images were taken and the parallax between cameras, realignment of images was

required before the differencing of the individual layers are computed to determine the signature of burns across all the spectral layers.

A total of 27 images were collected for each set on 10 porcine patients, including 8 MSI spectra, depth, visible light, and thermal. This image data was used in the machine learning to train the algorithms to recognize burn depth.

5. Automated Burn Recognition Algorithm (ARA, USAISR, OSU)

To predict burn depth, we required "ground truth" pictures of burn wounds. The original plan was to collect ground truth images in the form of annotated photos from the bedside. Since we were not able to collect prospective human patient images, we used historical burn images and had volunteer burn clinicians annotate these images online, using a web-based tool the Ohio State University (OSU) developed called, Label Coach. Label Coach was designed and constructed to meet this essential need of the project.

a. Porcine Burn Images

ARA evaluated the images from the porcine model collection for development of an ML algorithm to segment an image based on partial and full thickness burns. The data collected from these models was challenging to use because the MSI bands were very small. The MSI bands were originally selected based on previously published results from research conducted in a more controlled and better lighted environment. As a result, in our context the images were dark (less information content) and required longer exposure times (which increase blurring and motion).

ARA used a convolutional neural networks approach to automatically compute band combinations that revealed unique signals associated with the known burn mapping from the animal study. We were not able to identify a signal combination that generated a burn mask due to the limited available data. However, we made an incidental discovery that reveals tattoo ink, as shown in Figure 24 below.

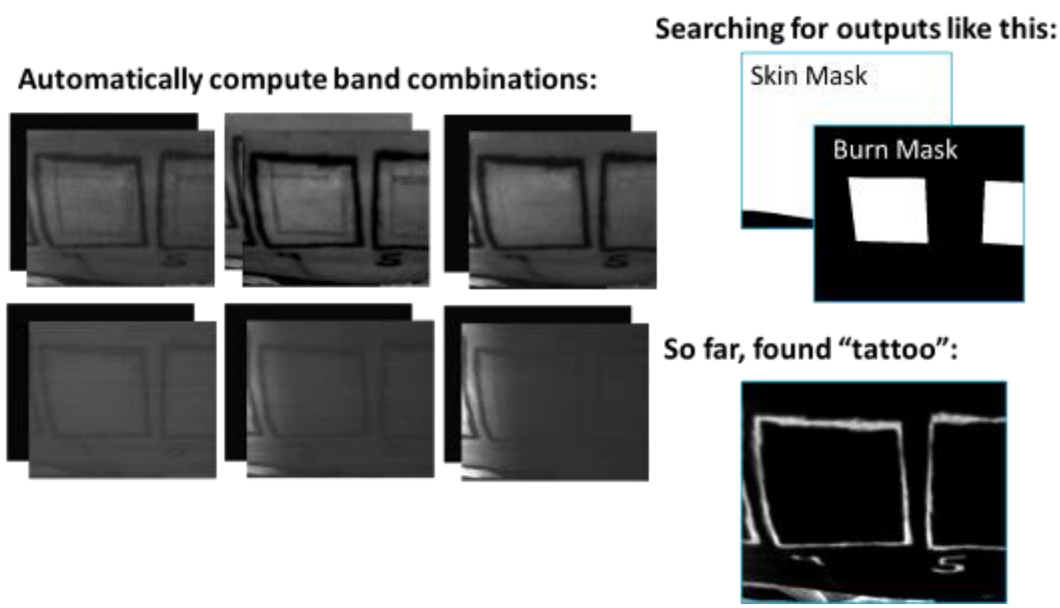


Figure 24. The MSI data from the porcine burns has not revealed any combinations that identify burn depth. However, we have found a combination that accurately labels the tattoo ink. This indicates that the approach is valid, but the spectral bands we are currently using either are not appropriate for burns under passive lighting conditions, or there is insufficient data within these spectral bands for analysis.

b. Human Burn Images

Concurrently with working the MSI-based approach on the porcine burn images, ARA investigated other ML approaches that could be used on the iPad or on pre-existing digital photographs. They discovered a semi-supervised approach based on our Skin Segmentation algorithm that enabled them to get results directly from color images (not requiring NVIR bands) based on identifying how likely a segment of the image was to have come from a class of images (in this case, they used the moderately burned de-identified patient data set from OSU and the severely burned de-identified patient set from USAISR, and an un-burned skin image set from the web). This approach provided a basic classification that worked for the extreme cases but was less likely to accurately characterize the nuances and grades within an image. To do this, ARA needed to train on the SME-labeled data set generated using the Annotation Tool described below. The ML researchers prepared for this as initial labels were made based on historic patients. These different approaches will all converge when we are able to take human patient photos using the MSI camera and have those images expertly annotated (***Figure 25***).

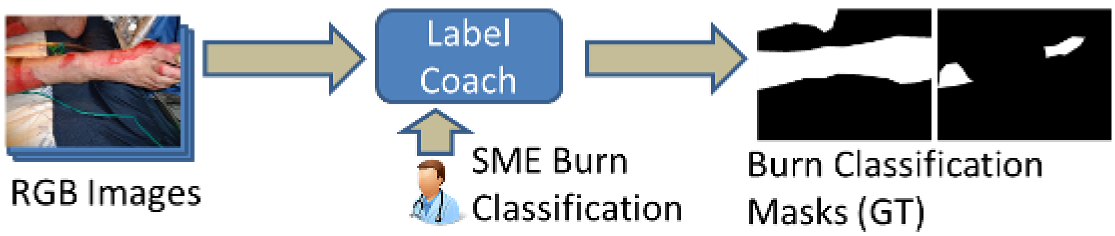


Figure 25. Human burn image classification process

ARA received a total of 1,176 patient images. This method presented a number of challenges since realistic identification of burn depth, particularly in separating partial and full thickness burns, requires touch. However, they were able to collect a total of 45 annotated images from 6 patients. It should be noted that three patient collections were twice-annotated by two different experts. Although the amount of training data was low, they boosted the number by using tiles and also transformed the images with respect to their extent while preserving the texture in general.

6. Development of the enhanced Lund & Browder Chart (ARA lead)

To assemble an eLB diagram, it was necessary to combine multiple images of the same patient onto a single diagram. Consequently, we either had to stitch the images together, or map them onto a single template. Below is a description of several techniques used during this study.

a. Image Stitching

We (ARA and USAISR) conducted a review of image stitching as a way to generate full body images of the patient for body mapping. Image stitching was necessary to connect multiple pictures of the same patient into a single registered image. If multiple photos of burn wounds were taken on a single patient, these images must be stitched to a common frame of reference, the burn wound image diagram. We tested two open source computer vision libraries, one was OpenCV and the other was BoofCV to support image stitching.

USAISR first took photos of a mannequin in the burn intensive care unit (BICU) using a blue background that enabled us to test the ChromaKey (also part of the OpenCV library) for a method of separating the patient from the background. Unfortunately, the mannequin had very few distinctive points for the stitching algorithm in either library to be able to stitch the images together so a fiduciary marker in the form of a QRF code was manually inserted on a photo of the trunk and the left arm. We ran the algorithm again using both BoofCV and OpenCV. OpenCV did slightly better at stitching the photos together. (***Figure 26***).

Figure 26. (LEFT) Mannequin arm with QRF marker, (CENTER) Mannequin trunk with marker, (RIGHT) images stitched together using OpenCV.

We took numerous photos of a human volunteer using four sheets with the QRF marker placed at the left shoulder, right shoulder, left hip, and right hip. However, based on this brief experiment, we determined that a unique marker is necessary for each location. USAISR also tested the Canny Edge Detection Technique (***Figure 27***). This was only partially successful in capturing all the edges of the body and was subject to multiple sources of error.

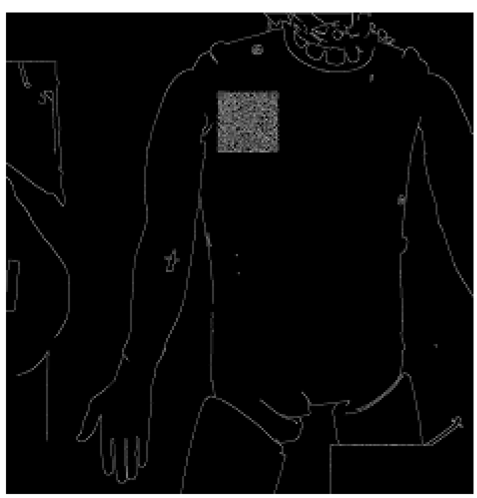


Figure 27. Body Silhouette using Canny Edge Detection.

In addition, we did a study on the effects of realistic perspectives (e.g., standing bedside) on the data when projected to a standard *LB* chart. We determined that in addition to image stitching (as we had previously done) we needed to adjust and combine multiple images to a 3D surface of the patient to be most accurate. We evaluated and selected a small depth sensor (Structure Sensor) and integrated this to our iOS application. As a result, the platform now captures both the RGB and depth data for each image.

b. Depth Image Data

To support better image composition, the depth data can also support improved segmentation of the patient image from the background. An example can be seen in ***Figure 28***. The first photo is a single RGB+D image taken from a position facing the subject. Notice that there is missing information on parts of the body surface that do not have line of sight to the camera. Next is the result of combining 2 RGB+D images, the additional perspective was similar to the view shown. Last is the results of rendering the same data from a third perspective for which there was no data initially collected. Working in 3D space like this would allow us to better remove the background and combine images taken from poses around the bedside (vice a camera mounted on the ceiling or held over the patient in the ICU).

A. Single Perspective (side view shows depth) B. Two Perspectives Combined (second is straight on) C. Same data rendered from novel third Perspective

Figure 28. Three images of the same subject/pose showing how perspective images can be combined in 3D space to generate a combined image from an entirely new perspective.

The research team at ARA, developed 3D mesh models of humans posed to correspond to the Pose Templates. These 3D meshes were used to provide a starting point for matching the observed scene with some positional and pose error. These models were based on a reduced quad count mesh from the open source system MakeHuman.org, we adjusted and posed them so that they align well to the templates. We have previously developed software that allowed us to take color+depth images that works with these.

The ARA research team investigated multiple "off-the-shelf" algorithms for 3D point cloud registration to align pictures/depth data from multiple perspectives. The benefit of projecting this data to 3D was so photos from multiple diverse perspectives could be combined into a single dataset that could be repositioned to achieve the full anterior pose used in the eLB. ARA performed their experiment in three steps: **Step 1**: process depth and color images to produce a 3D point cloud that removed image artifacts from perspective. **Step 2:** bring point clouds to a common frame of reference. **Step 3:** transform each set of points to register them to each other. Initial use of off-the-shelf algorithms such as Iterative Closest Point (ICP) and Super4PCS were investigated, but (as anticipated) they do not perform well because the images have minimal surface overlap. This was an anticipated issue, and their work with 3D meshes would help them resolve the issue. They worked on identifying known areas of anticipated overlap within each pose (e.g., marking the corresponding shoulder area for both the arm and chest poses) so that the point cloud registration could optimize on overlaps in corresponding areas instead of over the entire surface. See Figure 29.

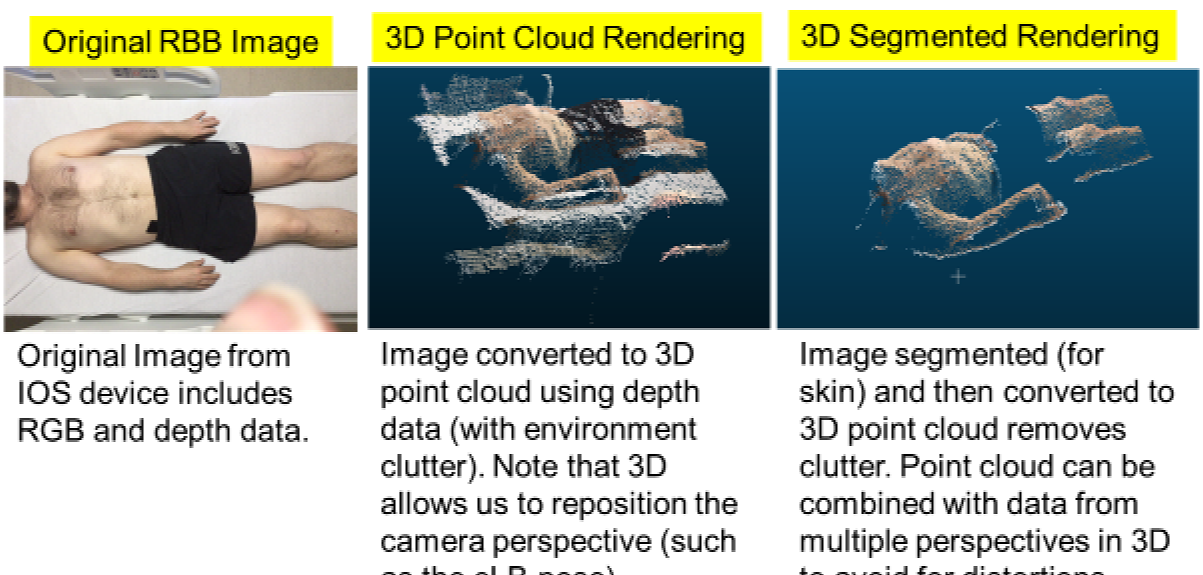


Figure 29. Combining depth and skin detection. Images taken with our sensors include both RBG (left) images and depth maps. ARA has developed software to convert these to a 3D point cloud (center) that can be rendered in 3D and rotated for multiple perspectives. We can combine our skin segmentation and the point cloud process to produce point clouds that reflect only patient skin (right).

Computational Neural Network (CNN)

Once the skin segmentation was complete, ARA used a CNN to map the image data to the correct places on the mesh. The CNN used the depth data to remap the image into a UV coordinate system. They used the pose template images from the volunteer subjects to teach the CNN to identify anterior and posterior images. The end result was the eLB, except the body morphology was standardized and did not represent the body morphology of the subject.

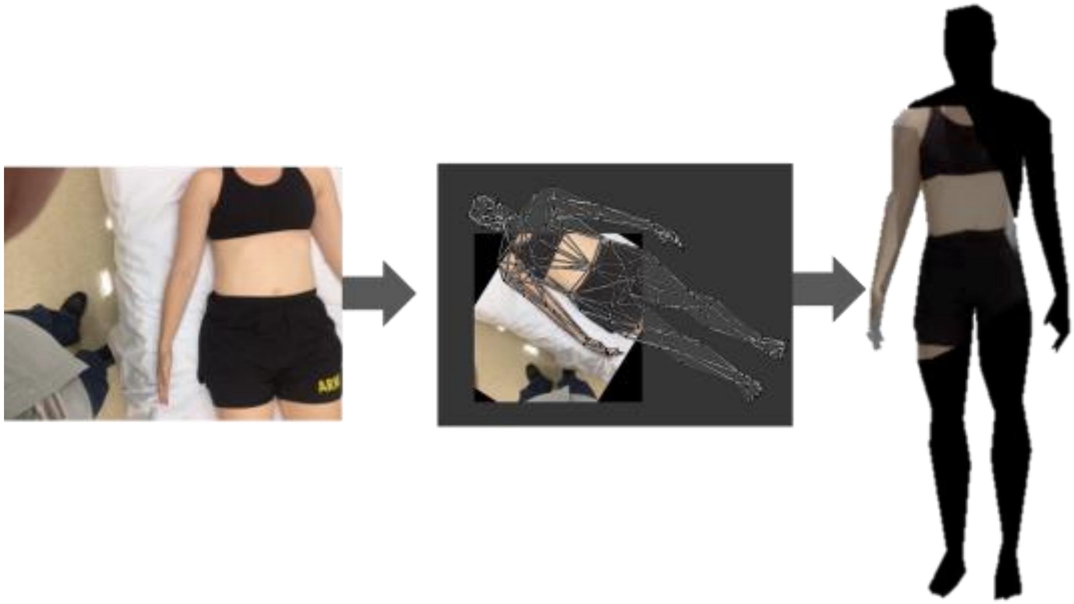


Figure 29. A neural network automatically maps the UV coordinate space (used for texture mapping) of a standardized 3D mesh to posed images. This allows us to "wrap" the 3D with 2D images.

The challenge here was the time required to produce training data, which required manually mapping coordinates.

7. Development of burn wound image annotation process

Expert annotated burn images were required for discerning different degrees of burns, burns from other wounds, and burn from blemish or shadow on skin. However, expert annotation was a time consuming and error prone process. In order to build a large collection of burn images with ground truth labels to be used for burn detection and classification research, we developed a cloud based tool hosted in Amazon Web Service, that allowed easy image annotation in many different and useful forms, called Label Coach. OSU was the lead for this effort. The online tool provided functionalities such as a painting and erasing brush, drawing polygons, querying images, and browsing the database (Figure 31). The annotation tool was based on react-redux web development framework which allowed us to implement feature-rich application with high level of flexibility and scalability observed in a single page application. The web-based image labeling tool was designed for administrators to maintain and manage annotators and the database as well as for the annotators to perform the manual labeling of the images. The USAISR clinicians and software engineers provided OSU with initial system requirements based on their experience using WoundFlow. WoundFlow was a burn wound mapping software system that was developed by USAISR software engineers and used by USAISR burn clinicians, from 2009-2015.

The Label Coach software had two components, namely the backend server and the front-end user interface or UX. The backend server was leveraged from other projects at OSU and used a powerful software infrastructure called Girder (from Kitware Inc.). The front end was designed with users in mind based on the feedback from USAISR clinical users. Choices of the viewport size, color schema, brush colors, types and sizes, and the display of meta information was being constantly explored for optimal user experience. The performance and robustness of Label Coach was also under scrutiny especially given the need to work in protected WiFi domains that was typical at USAISR and the Brooke Army Medical Center. Given various network controls (firewalls, authentication schemes, etc.), Label Coach was failing to operate continuously. We explored a number of ways to track and circumvent the problem, but were unable to do so.

Label Coach was necessary to support this project as existing tools did not address our requirements. Simply using Microsoft's Paint or Adobe's Photoshop was not feasible because their output formats were not amenable for straightforward inclusion in the usual machine learning and machine vision workflows. While Photoshop could export data to different image formats, it lacked the ability to preserve annotations present in separate layers, nor was it sufficiently user-friendly for clinicians to easily access and annotate images during the short periods of time when they were available. In addition, the use of these applications would require expensive setups and cumbersome user and storage management. An example of a comprehensive application platform for annotating and processing images of skin wounds and burns was WoundFlow. It was a standalone desktop application that required the installation of a backend database such as Oracle or MS MQL Server 2008 and was located in the development environment at the USAISR. Unfortunately, it saved all images locally and could not take advantage of the cloud and network infrastructure. ARA and OSU would not have had access to the data, making WoundFlow unusable for this project. Also, WoundFlow, did not allow the user to annotate depth of burn directly over the photo and the anticipated labor to alter the software to accommodate the BURNMAN project would far exceed the cost of developing Label Coach. Lastly, the open source program LabelMe, hosted by MIT was unable to meet our requirements since its use required the uploading of images to an external database in the cloud thereby losing control of the images and violating the controls mandated by the IRB for the collected burn images.

Therefore, we continued to improve the Label Coach software for collection of burn image annotations. USAISR clinicians periodically used the software to annotate burns on photographs of deceased patients. Select clinicians also provided user experience feedback to OSU and ARA regarding Label Coach's utility and functionality. The goal was to provide a robust and amenable way to delineate burn wounds on the patient as manifested in a photograph. The capture of extent, shape and texture of the burn wound was essential for the processing to follow.

Figure 31. Example screenshots of the annotation tool for helping expert clinicians identify the area and degree of the burn shown in an image. ML algorithms used this data to learn how to perform this annotation automatically. We will also use this data to evaluate the accuracy of the ML on data with "gold standard" answers.

When the annotator opened the page, a list of patient folders was displayed. Next, the annotator selected an image within a folder to start the manual labeling of burns. The annotator could select a brush tool along with its size and specify the label of the burn region. Labels could be one of these: normal skin (green), 2nd Degree-Partial thickness burn (yellow), 3rd degree-Full thickness burn (red), 4th degree-charred or burn to bone (orange). These labels were inspired from best practices of colleagues and experience using WoundFlow, at USAISR. The annotator freely annotated regions with a selected label on the image using the brush tool. Upon completion, annotated regions were recorded on the tool server and was displayed on the presented image and was viewable for administrator view. The annotator was free to label as many regions in the image as they chose. There was also an eraser tool which enabled the annotator to correct the labeled region as necessary. When the annotator was satisfied with the labeled regions in an image, they could proceed to label another image from the left thumbnails scrolling list. The resulting labels were stored in a JaveScript Object Notation (JSON) object format.

8. Development of an automated process for generating an eLB

Building an automated 2D eLB involved building models that collage and align the 2D images using homographies (coordinate transformations between different perspectives) to address differences in scale, translation, and perspective.

The algorithm development for registering images to the 2D eLB was demonstrated in ***Figure 30***, ***Figure 31***, and ***Figure 32***, including examples of different body types and subjects assembled from the pose templates.

Figure 30. 2D registered image built from 6 separate template photos.

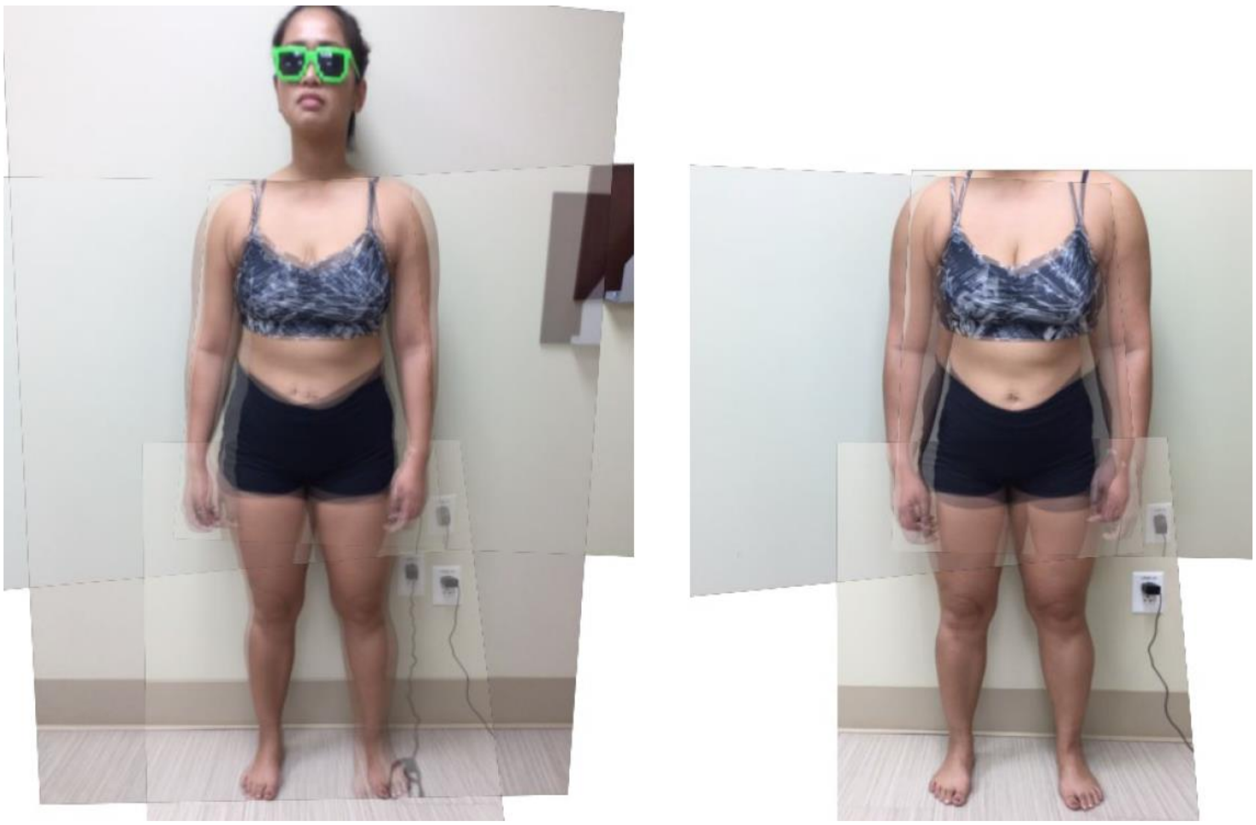


Figure 31. 2D registered image built from 6 separate template photos.

Figure 32. 2D registered image built from 6 separate template photos.

ARA implemented corrections for pose linking to account for the fact that natural poses were often not straight, especially when photos were of patients on their side in a bed. The natural pose was not straight due to bed sag, knee, waist, and neck bending, and collapse of the legs. They used detection of medical landmarks (green dots in ***Figure 33***), mapping the spline curve to landmarks, and then warping the image to straighten the spline.

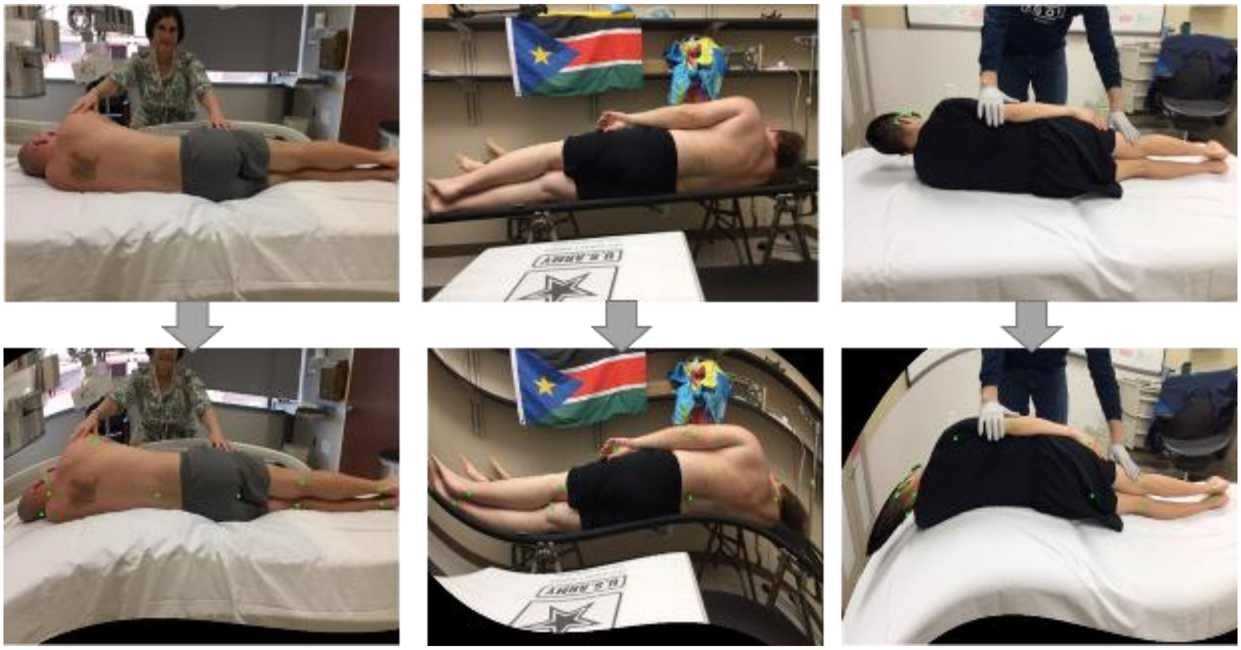


Figure 33. Spine to Spine Pose Correction on posterior images. Green dots on the images are used to identify medical landmarks.

To combine posterior images from a lying patient, they had to correct for the pose curvature. To do this they used the detected landmarks to register and crop images. However, in some images, landmarks were not detected correctly or at all.

Figure 34. Initial Posterior Image registration.

ARA tested methods to improve the initial image registration by including a color-based registration swap. In the sample image from ***Figure 34*** and ***Figure 35***, the pant and bra lines become better aligned. However, the patient width wa slightly reduced. This wa likely due to registering specular/shadow on the back from the overhead light source.

Figure 35. Posterior image corrected using color-based registration.

The final process, illustrated in

, takes raw RGB images, uses probabilistic detection to identify landmarks, and realigns based on the landmarks with the spline curve. It then generates a composite image by translating and warping the multiple poses/images.

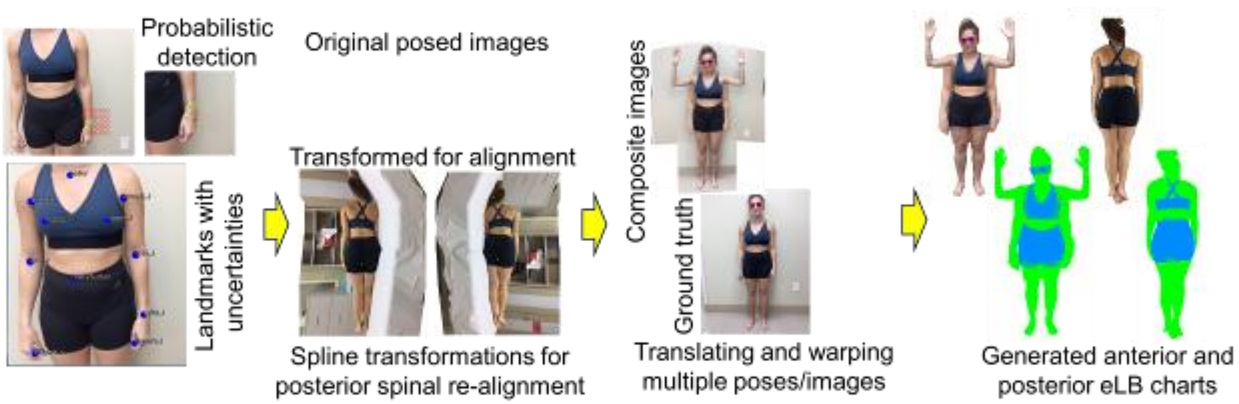


Figure 38: ARA created ML algorithms to automatically identify body landmarks in images and use them to align, scale, and reverse perspective distortions in collected images. They assembled these partial body images into full-body anterior and posterior images, called an "Enhanced Lund & Browder (eLB) chart," that was overlaid with burn classification data. From this eLB, they computed %TBSA based on actual patient morphology.

What opportunities for training and professional development has the project provided?

Every member of the research team has a better understanding of the practical and technical issues and challenges in trying to develop an innovative and positively disruptive technology to improve burn care of combat casualties. There is a greater understanding about computer vision and automating the process of burn image capture, annotating depth of burn wound and automatically calculating the TBSA burned. The work will lead to preparation of manuscripts in peer reviewed journals as well as be submitted to workshops and conferences. Further, this work can be used as the basis of graduate level theses and dissertations as well as serve as preliminary data for future research grants.

If an automated system for capturing burn patient images and assembling them into an eLB could be accomplished, the eLB could be automatically transferred to a digital Tactical Combat Casualty Card (TC3,) improving documentation on the battlefield. With further funding and development, this technology could potentially to train medics on burn patient management and wound identification.

How were the results disseminated to communities of interest?

During the project, we presented two posters at the Military Health Systems Research Symposium (MHSRS) in Orlando, Florida. We also presented a poster at the 2019 American Burn Association Conference.

We are developing at least one manuscript for publication in a peer reviewed journal, yet to be determined.

What do you plan to do during the next reporting period to accomplish the goals?

The project has concluded. However, a number of steps remain to successfully field this capability with military or civilian medics. Further data collection of annotated burn injuries is necessary to complete training of the algorithms for calculating TBSA. There may be a requirement for FDA certification of the predictive algorithm prior to fielding.

The final version of the application operates with RGB image data only. There is a significant potential that MSI data will improve the accuracy of the system in identifying burn wound depth. Collection of MSI image data for additional training of the ML algorithm is necessary to finalize this capability. Further, additional engineering design, such as minimizing the cube and weight of the MSI capability into a mobile platform, is needed to enable fielding.

4. IMPACT:

What was the impact on the development of the principal discipline(s) of the project?

The results of this research were delivered in the form of software in conjunction with a camera that can identify burn injuries and automatically calculate the total body surface area burned. This will improve burn fluid resuscitation, burn patient outcomes, and may save lives in a prolonged care environment by increasing the efficiency of triage and resource use, and preventing individuals from being overestimated and inadvertently put into the expectant category. This will help with burn care on the battlefield, in US rural hospitals and in burn centers across the globe.

The current system will enable efficient burn and wound image data collection in healthcare settings. This image data, once annotated, would serve as ground truth to improve the accuracy of the algorithms for calculating TBSA for burns, or identifying other wounds types and affected body regions.

Data collection for training the ML methods will require scrutiny given the large variation of “burns” and the confounds that will impede classification.

What was the impact on other disciplines?

Nothing to report.

What was the impact on technology transfer?

The ability to computationally identify burn injuries has eluded the medical community possibly due to the complex nature of the wound, with few characteristics in the visible spectrum that uniquely differentiate a burn from other types of wounds. By using MSI and RGB images, we have started building algorithms to differentiate types of burns from background and healthy skin. The product of this study may have a large impact on the prognosis of burn patients in both the civilian sector and the military. By providing improved capability to untrained medics and EMTs to assess burn patients, we could potentially reduce the potential for treatment error with this vulnerable patient type.

What was the impact on society beyond science and technology?

Nothing to report.

5. CHANGES/PROBLEMS:

Changes in approach and reasons for change

RVS was originally going to make reference design, but contract negotiations with ARA were not successful. As a consequence of this, ARA was supposed to provide the reference design. However, due to decreased funding, a SOW change and a contract modification, ARA was no longer contracted to make a reference design. The Reference Design was determined to be unnecessary as the final report would include all performance specifications for the system that will be necessary to generate a CDD and publish an RFQ to manufacturers to fabricate the final device.

The decision not continue with WoundWise also impacted the project. The inventor/collaborator who was supposed to be on our project, left OSU. Also, after an indepth analysis of the WoundWise software, it was determined that in its current state, it was not adequate to meet the goals of the project.

Actual problems or delays and actions or plans to resolve them

After much discussion between JPC1, USAMRAA and USAISR, it was decided 3 months after USAISR received funding for this project, that USAISR would need write a contract in order for ARA to do the work for this grant. Unfortunately, putting ARA under contract took approximately 6 months, resulting in ARA not being on contract for 9 months after USAISR received the funding.

IRB approval for human use protocols was expected to take 90 days. However, 2 of the three protocols we were running were not considered human use research, but had both taken over 120 days to secure a determination from the IRB. Long turnaround times from the regulatory compliance office and the IRB have been common as we have worked on these non-human use protocols.

This study ended up being a bottom up development project because RVS NVIR camera and WoundWise technologies were not used in this project. Unfortunately, it took 18 months (out of the 24 months of the POP for the ARA contract) of research and development before the technology was mature enough to use in an IRB approved protocol using burn patient data. With only 6 months left on ARA's contract, there wouldn't be enough time to get an IRB approved protocol for prospective burn patient data collection done. Therefore, this task was not accomplished. We worked around this by collecting animal and non-patient human subject volunteers' data as the BURNMAN technology was being developed, to train the body recognition algorithms to assemble the eLB. In order to train the algorithm on burn recognition, we used a combination of porcine burn wound images collected from a series of on-going animal use protocols, and a collection of over 1,500 historical burn images from USAISR and OSU.

Changes that had a significant impact on expenditures

The removal of RVS from the project team had some effect on the delivery time of the MSI camera to ISR. The MSI camera that was delivered was not usable and required a hardware platform and software to be built. This also reduced the rate of ARA's expenditures for the work in year 1 and impacted the timeline.

The original PI from OSU who was the inventor of WoundWise, left OSU before the start of the project. ARA attempted to still get access to WoundWise so it could be modified by our other OSU collaborators, but those negotiations were unsuccessful. This significantly delayed getting OSU on contract with ARA. Therefore, in collaboration with ARA and USAISR, OSU had to do a bottom up build (based off their experience developing WoundWise) to develop a brand-new burn annotation tool, called LabelCoach. Building LabelCoach took over 6 months and was housed in AWS cloud. Unfortunately, accessing the software from AWS was inconsistently reliable when used on government computers by USAISR clinicians, secondary to DoD firewalls/cybersecurity rules. This did not impact expenditures, but it did impact the timeline.

Significant changes in use or care of human subjects, vertebrate animals, biohazards, and/or select agents

We received approval of an amendment adding BURNMAN personnel to an animal use protocol for a burn study on swine, enabling us to capture burn image data on the swine.

Protocol [ACURO Assigned Number]: # A1730

Title: Optimization of Debridement Depth that Results in Complete Graft Take for Porcine Burn Wounds

We have received two Non-Human Subjects Research determinations for data collection using historical burn photos and volunteer photos.

Significant changes in use or care of human subjects

See above regarding planned prospective burn patient data collection.

Significant changes in use or care of vertebrate animals

Nothing to report

Significant changes in use of biohazards and/or select agents

Nothing to report

6. PRODUCTS:

- **Publications, conference papers, and presentations**

Journal publications.

Nothing to report

Books or other non-periodical, one-time publications.

Nothing to report

Other publications, conference papers and presentations.

MHSRS Poster 2018 "Challenges in Automating the Characterization of Burn Injuries for Pre-Hospital Care" Won honorable mention in category

American Burn Association Poster 2019 "Automating the Characterization of Burn Injuries for Pre-Hospital Care"

MHSRS Poster 2019 "From Admission Photos to an Enhanced Lund Browder Diagram: Automating Accurate and Timely Burn Wound Annotations"

- **Website(s) or other Internet site(s)**

Nothing to report

- **Technologies or techniques**

We developed pose templates software of 13 common poses used while taking admission photos of a burn patient. The software is on an iPad Mini with a Structure sensor. This software is intuitive and easy to use and assists the clinician in taking burn photos. The system captures RGB and depth data that can be stored either locally on the iPad Mini or on the BURNMAN server once internet connectivity has been established. This system could enhance capturing burn patient admission photos in future research studies.

We have developed a novel semi-supervised machine learning algorithm that is able to differentiate patient skin surfaces from artifacts (called segmenting the skin) in the RGB photo taken with the iPad mini and Structure sensor. This is critical for extracting the patient outline for the eLB that can potentially be included on a digital TC3 card.

We also developed a novel semi-supervised machine learning algorithm to identify patient body regions and assemble various photos of a patient into a single patient diagram, similar in shape to the patient. The eLB is also suitable for annotation of injury and automatically calculating the TBSA burned which could also be potentially included on a digital TC3 card.

- **Inventions, patent applications, and/or licenses**

  Nothing to report

- **Other Products**

MSI Camera system: MSI Camera, touch pad, and Real Sense depth camera mounted on a single hand-held mount for data collection.

Data capture software: iOS and Windows software for applying a template over the image from the camera to enable clinicians to take the correct pose for photo capture.

Annotation Software: LabelCoach allows users to map depth of burn directly on top of an RGB photo of a patient.

7. PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

What individuals have worked on the project?

Name: Maria L. Serio-Melvin
Project Role: Co-PI
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1 person-month
Contribution to Project: Responsible for overall conduct of the grant and ISR research protocols, provided leadership for diverse team located across the United States, provide burn subject matter expertise.

Name: Jeremy Pamplin, MD
Project Role: Co-PI
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1 person-month
Contribution to Project: Responsible for overall conduct of the grant and ISR research protocols, provided leadership for diverse team located across the United States, provide burn subject matter expertise.

Name: Jose Salinas, PhD
Project Role: Contract Officer Representative, Associate Investigator

Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1 person-month
Contribution to Project: Worked with ARA to ensure they were delivering on key in the contract; provided subject matter expertise on software development, assisted the PI in project management

Name: Craig Fenrich, BS
Project Role: Senior Biomedical software engineer
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1 person-month
Contribution to Project: Did initial testing of cameras, SDK to determine best technologies to use for BURNMAN project. Provided requirements and consultation for LabelCoach annotation tool.

Name: Jeff McCorcle, PA
Project Role: Senior Surgical Physician Assistant, USAISR Burn Center
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: .03 person-month
Contribution to Project: Provided burn subject matter expertise, especially on burn wound care and determining depth of burn and annotating burn images.

Applied Research Associates (ARA) :

Name: Christopher Argenta
Project Role: ARA PI
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1 person-month
Contribution to Project: Chris has organized image expert support, reviewed camera options, and reviewed all data generated by USAISR for image stitching and body mapping work.

Name: Gregory Rule
Project Role: ARA PM
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1
Contribution to Project: Greg has managed the contract reporting, subcontracting with OSU, and purchasing. Greg also hosted all project meetings supported work at USAISR to test out camera solutions in the Burn ICU.

Name: Margaret Pediaditakis
Project Role: Administrator
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1
Contribution to Project: Project administration

Name: Greg Federaro

Project Role: Imaging platform optimization
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1
Contribution to Project: Imaging technology development

Name: Michael Henson
Project Role: Imaging platform optimization
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1
Contribution to Project: Imaging technology development

Name: Thomas Miller
Project Role: Imaging platform optimization
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 0.03
Contribution to Project: Imaging technology development

The Ohio State University (OSU)

Name: Raghu Macchiraju
Project Role: OSU Co-PI
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1 person-month
Contribution to Project: Raghu is the technology lead of the OSU component of BURNMAN. He is responsible for the OSU tasks pertaining to Objective 2 and 3.

Name: Asmaa Aljuhani
Project Role: Programmer/Scientist
Researcher Identifier (e.g. ORCID ID): NA
Nearest person month worked: 1
Contribution to Project: Asmaa works closely with Raghu on developing algorithms.

Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period?

The team from WoundWise, Chandan Sen and Brent Toto did not participate in the project since they were no longer employed at Ohio State.

What other organizations were involved as partners?

Provide the following information for each partnership:
Organization Name: Ohio State University
Location of Organization: Columbus, OH

Partner's contribution to the project

- *Facilities (e.g., project staff use the partner's facilities for project activities);*
- *Collaboration (e.g., partner's staff work with project staff on the project);*

OSU is collaborating on the project, developing the burn wound annotation tool and generating automated edge detection of burn wounds.

8. SPECIAL REPORTING REQUIREMENTS

COLLABORATIVE AWARDS: For collaborative awards, independent reports are required from BOTH the Initiating Principal Investigator (PI) and the Collaborating/Partnering PI. A duplicative report is acceptable; however, tasks shall be clearly marked with the responsible PI and research site. A report shall be submitted to **https://ers.amedd.army.mil** for each unique award.

QUAD CHARTS: If applicable, the Quad Chart (available on https://www.usamraa.army.mil) should be updated and submitted with attachments.

9. APPENDICES: Attach all appendices that contain information that supplements, clarifies or supports the text. Examples include original copies of journal articles, reprints of manuscripts and abstracts, a curriculum vitae, patent applications, study questionnaires, and surveys, etc.

BURNMAN is at a TRL 4-5. We (ARA and USAISR) have demonstrated BURNMAN to high ranking civilians in MRDC as well as visiting generals and CSMs.