Acta Astronautica 200 (2022) 262–269

Contents lists available at ScienceDirect

Acta Astronautica

journal homepage: www.elsevier.com/locate/actaastro

Research paper

Automated identification of astronauts on board the International Space Station: A case study in space archaeology

Rao Hamza Ali [a], Amir Kanan Kashefi [b], Alice C. Gorman [b], Justin St. P. Walsh [a], Erik J. Linstead [a,*]

[a] Chapman University, Orange, 92868, CA, USA
[b] Flinders University, Adelaide, 5042, South Australia, Australia

ARTICLE INFO

Keywords:
International Space Station
Deep neural networks
Face detection and identification
Amazon rekognition API
Social analysis
Computer vision

ABSTRACT

We develop and apply a deep learning-based computer vision pipeline to automatically identify crew members in archival photographic imagery taken on-board the International Space Station. Our approach is able to quickly tag thousands of images from public and private photo repositories without human supervision with high degrees of accuracy, including photographs where crew faces are partially obscured. Using the results of our pipeline, we carry out a large-scale network analysis of the crew, using the imagery data to provide novel insights into the social interactions among crew during their missions.

1. Introduction

"It's been very interesting to see the perspective of being on the space station throughout all those different regimes. I was always the one that had arrived most recently. And now I am the lead of the US-operated segment, and I have a little bit more responsibility because of that position. It feels a lot more like ***my*** *mission now." - Jessica Meir [1]*

This paper introduces the concept of using computer vision for the identification of astronauts in photographs taken on the International Space Station. These photographs are the one of only a few sources for measuring the interactions between astronauts. Using the tagging system introduced in the article, over 240 astronauts can be identified in photos, allowing the reconstruction of networks of astronauts that help us define and understand intra- and inter-agency interactions in space.

The International Space Station (ISS) is an orbital living and working environment which has been inhabited for twenty-two years [2]. First launched in 1998, the ISS is a multinational collaborative project involving five participating space agencies: National Aeronautics and Space Administration (NASA; United States), Roscosmos State Corporation for Space Activities (Roscosmos; Russia), Japan Aerospace Exploration Agency (JAXA), European Space Agency (ESA), and Canadian Space Agency (CSA) [3]. As of today, there have been more than 240 visitors to the ISS from nineteen countries.

A perennial question for crewed space missions, and in general for remote research stations whether on Earth or in space, is how the social life of the crew can be maintained in a harmonious state and contribute to mission success. ISS serves as a research facility and laboratory and the astronauts and cosmonauts on board conduct experiments and research in physical sciences, material science, life sciences, and human studies [4]. The ISS today is inhabited by a crew of seven members [5], each working around 6.5 hours each day, conducting experiments and performing station maintenance [6]. While the crew follows a routine that would not be out of the ordinary on Earth in terms of work hours, a sleep schedule, access to food and amenities, etc, life in space can be a fascinating spectacle. Crew members are among the best in their fields and undergo grueling training for years in hopes for a selection to an expedition. On the station, they live in micro-gravity and conduct cutting-edge research on a daily basis, all the while orbiting Earth at a speed of 7.66 km/s [5].

The International Space Station Archaeological Project (ISSAP) has worked since 2015 to understand the social and cultural structures of ISS, the first permanent human habitat in space [7–10]. By directing attention to these features, we are developing data-driven insights that can improve the experiences of future space station crews. We categorize our approach as archaeological as it revolves around two central themes in the contemporary study of material culture: objects and environment (especially built spaces). We liken the environment to the social structure on the space station, which can be defined by paired frequencies of astronauts photographed together. Interviewing every single astronaut that had once inhabited the space station, regarding their interactions with their colleagues, is not feasible and, in any case, can be marked by the fallibility of recollection common to all humans. Anecdotes cannot compare to direct observation as a source for data. Thus, analyzing crew behavior, and the environment, through the lens

* Corresponding author.
E-mail address: linstead@chapman.edu (E.J. Linstead).

https://doi.org/10.1016/j.actaastro.2022.08.017
Received 28 December 2021; Received in revised form 11 June 2022; Accepted 8 August 2022
Available online 12 August 2022

of interactions captured on camera, helps develop an understanding of the material culture.

Archaeologists have traditionally been early adopters of digital methods of recording and analysis, with the Computer Applications in Archaeology group being established in the UK in the 1970s, which soon evolved into a global event [11]. These applications have included Geographical Information Systems (GIS), statistical analysis, predictive modeling, and digital reconstruction of sites and artifacts [12]. Use of digital technology enables large scale spatial analyses and enhanced interpretation of archaeological sites. From the use of aerial photography to map sites [13,14], to high-resolution laser scanning and 3D modeling [15,16], and now the abundance of specialized computer-based analytical tools, digital technology has opened new realms of analytical possibilities [17]. Neural networks, which are computer models trained to detect objects, faces, labels, and other hidden features in data, have been developed to solve a wide range of detection and identification problems [18]. In archaeology, neural networks are deployed to identify objects in photos from excavations and can be trained to pick out patterns that otherwise would be laborious to identify manually. However, machine learning techniques have rarely been used for the analysis of the archaeology of the contemporary past. For our study, we use neural networks that are able to identify faces of astronauts in the photos, to make inferences about social behavior on the ISS, as a novel addition to digital archaeology.

NASA uses various social media platforms to engage with the public regarding the life on the ISS. The space station's Twitter account (@Space_Station) posts videos and updates regularly about the day-to-day activities on board the ISS and boasts 5.5 million followers [19]. The station's Instagram account (iss) has 7.8 million followers [20], where routinely-posted photos of the ISS and crew shed light into the intriguing life in space. NASA also conducts educational programs where crew members are able to have a live chat with students, answering questions related to research, space exploration, and their daily routine. Public engagement of this extent shows a deep level of interest about the life of humans on board the ISS. For those more interested about the photographs capturing the lives of astronauts on board the space station, the NASA Johnson Space Center Flickr account (nasa2explore) manages a significant collection of photos from space missions and expeditions dating back to the 1960s. The account has so far posted 56,169 photos that have received a total of 179.8 million views worldwide [21]. Capturing training on Earth and missions docking on the ISS, and portraying astronauts working in the space station, these photos provide a visual timeline for each space mission.

If we focus only on the photos taken inside the ISS, we manage to see how astronauts use the space around them, what they work on, and who they work with. Each photo on Flickr is accompanied by a caption that explains the context and lists the astronauts photographed. Parsing this information makes it possible to construct a database that helps answer questions such as which astronauts are photographed on board the ISS, in what locations, and who are they photographed with most. These questions help us understand the social environment on the ISS and can shed some light on how astronauts from different agencies interact with each other while they work on their designated tasks.

The photos posted on Flickr, however, are just a subset of an entire collection of photos taken on board the space station, numbering in the millions [22]. The rest of the collection is not shared with the public because it contains duplicate photos, photos showing materials or equipment that is sensitive or proprietary, or simply because the photos do not communicate the desired message about the ISS project. Protecting crew privacy is also a major concern in selecting the images which can be released to the public. As part of an ongoing effort to study the material culture of the International Space Station, NASA provided us access to a previously unpublished set of photos from the first seventeen expeditions to the ISS. These photos can be used to further validate the social structures gleaned from the Flickr photos. The informative captions provided, however, for NASA photos on Flickr, are not available for the unpublished photos. So in order to conduct an analysis on astronaut presence in photos and what sets of astronauts are photographed most in these images, we use a machine learning technique to automatically tag each astronaut in a photograph. Machine learning is a branch of artificial intelligence (AI) and an important component of data science which focuses on the use of data and algorithms to imitate human intelligence. Through this imitation, machine learning algorithms gradually improve accuracy and adapt to new data. With the help of machine learning, our study now becomes an application of digital archaeology with a set of unlabeled photos as the source we want to catalog. Correctly labeling these photos will help us further extend our knowledge on life on board ISS and how new and returning crew members develop social relationships with each other.

As will be seen, this study not only extends the capabilities of archaeology by providing a new method for others to use, it also provides a window into the significance of the timing of crew arrivals and departures for formation of relationships between individuals, as well as the relationships between crew from different agencies on the same missions. It therefore should be taken into account by current and future mission planners who want to optimize crew well-being and productivity.

2. Data

As mentioned previously, the NASA Johnson Flickr account contains a substantial collection of photos that are arranged in separate albums by expedition. Not only does the account host photos of astronauts on board the space station, the albums also contain photos taken during press conferences, preflight protocols, mission launch and undocking, and photos of Earth taken from ISS. From these albums, 8,291 photos show the interior of the space station, and of those, 7416 have captured at least one astronaut. To automate image and caption extraction of these 7416 photos, we designed and implemented a web scraping tool, using the Java programming language [23]. A web scraping tool processes web contents, finds data of interest, and stores them [24]. Using the Flickr API [25], we requested photo data and parsed the caption to recognize astronaut names. Images that did not contain any astronaut names were discarded.

Next, we manually checked each image and its caption to ensure that the astronauts mentioned in the caption could in fact be seen in the photo. Fig. 1 is a photograph from Expedition 26 and its caption reads *"European Space Agency astronaut Paolo Nespoli, Expedition 26 flight engineer, is pictured in the Cupola of the International Space Station. Nespoli and NASA astronaut Catherine (Cady) Coleman (out of frame), flight engineer, operated the Canadarm2 controls inside the Cupola to relocate the Japanese Kounotori2 H-II Transfer Vehicle (HTV2) from the Harmony node nadir port to Harmony's zenith port"* [26]. It is clear that astronaut Catherine Coleman cannot be seen in the captured image. For such instances, we discarded the names of astronauts that were not present in the photos. This was an important step as we looked to create an automated process to label the astronauts found in photos of the ISS. These images, combined with their captions, act as the ground truth for our algorithm, and are henceforth termed as the *Flickr captioned photos*.

Between 2019 and 2021, we were able to procure an additional set of photographs from NASA, for Expeditions 1–17. These photographs are a subset of all photos captured related to the expeditions but were not released to the public. As these photographs are not accompanied by captions, they act as the validation set for our algorithm. We want to first ensure that the algorithm performs well identifying astronauts in the *Flickr captioned photos*, before it can be run on these photographs. We will use the term *unpublished photos* to reference these images.

Fig. 1. NASA Johnson. "iss026e028062" 18 Feb 2011. Online image. Flickr. 17 Oct 2021.

3. Methodology

3.1. Neural networks

Identification and comparison of human faces is a problem that is relatively easy to solve using neural networks. Recent research has shown that neural networks are able to make predictions on face identification with an accuracy of 98.98% [27]. Neural networks are complex mechanisms that require a great deal of attention when it comes to training them to solve a particular problem. The architecture of the network, the nature of the data, the targets to be identified, and the technical capabilities of the machine being used, all have equal importance in successfully training a neural network to perform a task accurately. With image classification and object detection becoming more mainstream, there is an abundance of architectures one can use to create a simple classifier [28]. Processing powers of computers are no longer an issue, with Graphic Processing Units (GPU) optimized to aid the training process. While large images can be resized to smaller dimensions to speed up the training process, it is the size of the data set that now proves to be an issue that, at times, cannot be resolved at all. Data augmentation can be employed to increase the size of an image data set, which involves slightly manipulating the image (cropping, rotating, changing colors etc.) to create a new data point for the set.

When training a neural network, the computer model is given a set of "ground truth" images so that the network can make predictions about an image and measure how accurate it was in its prediction. As the network predicts and measures its accuracy, it is able to update weight values, through a process called Backpropagation [29], so that it can predict at a slightly higher accuracy the next time it sees the ground truth images. The number of ground truth images required for this training process scales with the number of objects, or in our case, astronauts, that we are trying to identify in each photo. In order to identify more than 242 faces, training a neural network from scratch would require significantly more than the 7416 *Flickr captioned photos* available.

To add to our ground truth image set, we considered scraping photos of astronauts from the web; but it was clear early on that we would not be able to procure a diverse set of photos for each astronaut that would boost our image data significantly. The possibility also existed of using transfer learning: a process that allows pre-trained neural networks, with updated weight values, to be modified slightly to cater to a different dataset [30]. So while the original neural network could be trained to identify faces in a set of images, it could easily be retrained to do the same for a completely different set of images. This step would still require a training process, albeit using fewer images. However, the orientation of astronauts' faces in photos taken on board the ISS made it a similarly difficult task. Fig. 2 shows a set of photos where astronaut Luca Parmitano was mentioned in the respective captions but his face has varying degrees of visibility. Face detection and identification with different levels of visibility, mainly due to the orientation of the face, is a relatively new field of research and has been shown to require a large set of input data for an accurately trained neural network [31]. We will describe the effectiveness of our approach with varying orientation of astronauts' faces in a later section.

Given these limitations, we opted for Amazon's Rekognition API [32] for our face detection task. This API provides scalable machine learning functionalities that can be used to identify people, objects, texts, and activities in images and videos. One of the core offerings of the API is facial recognition and analysis, which is done using neural networks that have been trained on millions of photos. A transfer learning stage is not required as the networks are trained to identify faces using pose-invariant (i.e, irrespective of orientation) features. With the ability to not only identify where a face is in a photograph but also to whom it belongs, as well as comparing that face with a set of other faces, if direct identification is not possible, the Amazon Rekognition API becomes the backbone of our tagging system.

Of the several features the API provides, we used the *Celebrity Recognition*, *Facial Analysis*, and *Face Comparison* functionalities for our tagging system. The *Celebrity Recognition* function, which is trained to identify the faces of popular personalities, was used to check if a crew member could be directly identified. During an initial experiment to test the capabilities of this function on our image set, Rekognition was able to identify only a handful of astronauts, those who have been in the public eye for a long time. For the remaining astronauts, we used the *Facial Analysis* and *Face Comparison* functions to identify them in photos of the space station.

3.2. Use of expedition contexts

Our earliest approach involved identification of a face in an image and use of the *Face Comparison* function of the Rekognition API to compare that face against all astronauts in our set. Eventually, the face would be identified; but it would require us to compare each face in an image, against 242 faces (one per astronaut). This resulted in an expensive and time-consuming process, given that the API costs scale with the number of images compared. To keep the costs to a minimum and to expedite the processing times for each image, we employed two techniques.

First, if the astronaut in a photo was not recognized using the *Celebrity Recognition* function, we passed the image to the *Facial Analysis* function to extract key information about each face identified. The *Facial Analysis* tool provides information on the orientation of the face (pitch, roll, etc.) and it further gives a probability of the gender classification of the person based on their face, with high accuracy. Over the first 63 expeditions to the ISS, there have been 204 men and 38 women on board the space station [33]. For a face not identified by the *Celebrity Recognition* function, we used its detected gender to limit which astronauts' faces it should be compared with. Through this addition, we significantly lower the number of comparisons needed, especially if the identified face is that of a female.

It is important to note that neural network based face-recognition algorithms have shown to more accurately identify the gender of light-skinned males, and perform worst with faces of dark-skinned females [34]. While the pool of astronauts is predominantly represented by Caucasian men, we threshold the gender detection (at 85%) to ensure that the gender feature is used only when the classifier is very confident about the detection. Furthermore, *Face Comparison* function avoids face recognition entirely, and is used to compare features across faces only.

Next, if a photo contained more than one astronaut, and some of them were detected by the *Celebrity Recognition* feature, we used

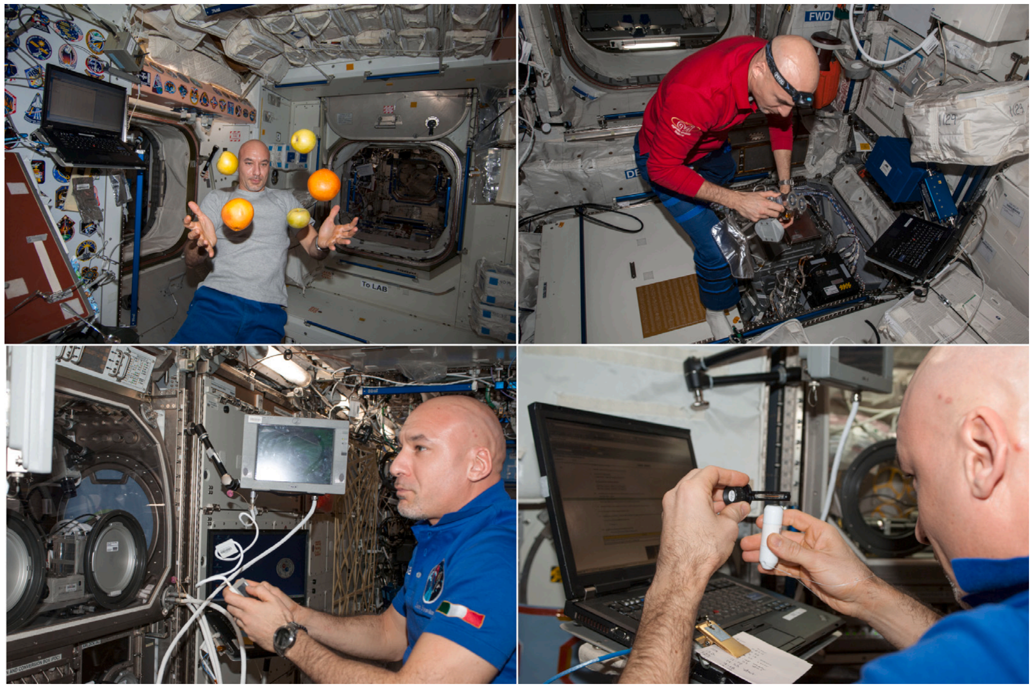

Fig. 2. NASA Johnson. Photos of astronaut Luca Parmitano with varying degrees of visibility. Online images. Flickr. 31 Oct 2021.

the information of those detected to create a small pool of potential astronauts that also might be in the photo. To do this, we manually created a database which stores information about each astronaut's travel to and from the space station. We used different Wikipedia articles and NASA records of ISS travels and expeditions to determine the flight times of astronauts for all expeditions to date. If two astronauts have an overlapping time range in the database, it means that they may have interacted on board the space station and could have been photographed together. Hence, a photo where we have identified one astronaut could potentially also include the other astronaut. Generating potential pools of astronauts, using flight data, allowed us to reduce the number of comparisons we made to an average of 5, compared to the original 242 count per photo.

Combined, these two added features enabled a tenfold decrease in the time and costs of processing the *Flickr captioned photos*. Fig. 3 provides the working of the tagging system in detail. We recorded all names of identified astronauts per photo in a file and used it to measure the accuracy of our tagging system.

4. Results and discussion

Across 7416 *Flickr captioned photos*, in which a total of 12,484 individual faces were detected, our tagging system was able to identify astronauts with an accuracy of 78.69%. The photographs were passed as input to our tagging system one by one, and the algorithm automatically determined the best route to identify each face found in them. To measure this accuracy, we compared the names of the astronauts cited in a photo caption to the names of those detected by the system. Here we assume that each astronaut in a photograph was also mentioned in the image caption. We did, however, find 44 instances where an astronaut identified in the photograph was not mentioned in the image caption. Fig. 4 was posted on Flickr with this caption: *"NASA astronaut Mike Fossum, Expedition 28 flight engineer, works among stowage containers in the Leonardo Permanent Multipurpose Module (PMM) of the International Space Station"*. [35] The tagging system was able to identify astronaut Satoshi Furukawa, outlined in red behind Fossum's hand, in the background. This underscores the effectiveness of our automated tagging system over manual astronaut inclusion in image captions.

Fig. 5 shows an illustration of the key features of a face pose. The yaw, pitch, and roll attributes determine the orientation of a face in three dimensions and are crucial in determining whether a face can be identified through an automated system. If the face is turned away from the camera, in the exact opposite direction, then a manual process will be needed to determine to whom the face belongs to. If some key features of the face (eyes, nose, mouth etc.) are at least partially in view, then it becomes possible to identify the face using our system. *Flickr captioned photos* do not always show astronauts looking straight at the camera. Instead, the astronauts are often photographed working and are focused away from the photographer. In fact, only 55% of all faces detected were oriented towards the camera (yaw +−30, pitch +−15). While the tagging system is able to identify a face that is slightly oriented away from the camera, a large percentage of wrong identifications were for faces looking away from the camera, or those that were obscured by objects in the photograph.

To measure the accuracy of the tagging system on the *unpublished photos*, we manually identified astronauts pictured in 475 images from the set. Next, we used the tagging system to classify those photos for astronaut identification. The tagging system identified astronauts with an accuracy of 92% with no misclassifications. The higher accuracy is due to the higher quality of the identification set as we had to first manually identify astronauts, and we could only do so for images where facial features were apparent. This small experiment was conducted to set up a baseline of how well the tagging system will perform on all photos and could be used in-house by NASA or any other entity to automatically tag photos going forward.

We will now discuss some applications that are made possible by the results of the tagging system. These applications contribute to determining the overall social structure on board the space station, and reveal some key points about inter-agency interactions. Note that while the analysis relies on the identification of individuals in the images, the data presented is anonymized as far as possible to protect crew identities. As these analyses use the *unpublished photos*, we are unable to publicize the astronauts captured in them. Furthermore, the analyses ascertain the interactions between astronauts, and beyond the scope of the space agency, their identities are not relevant. This type of approach can also be used for similar studies, where interactions between entities

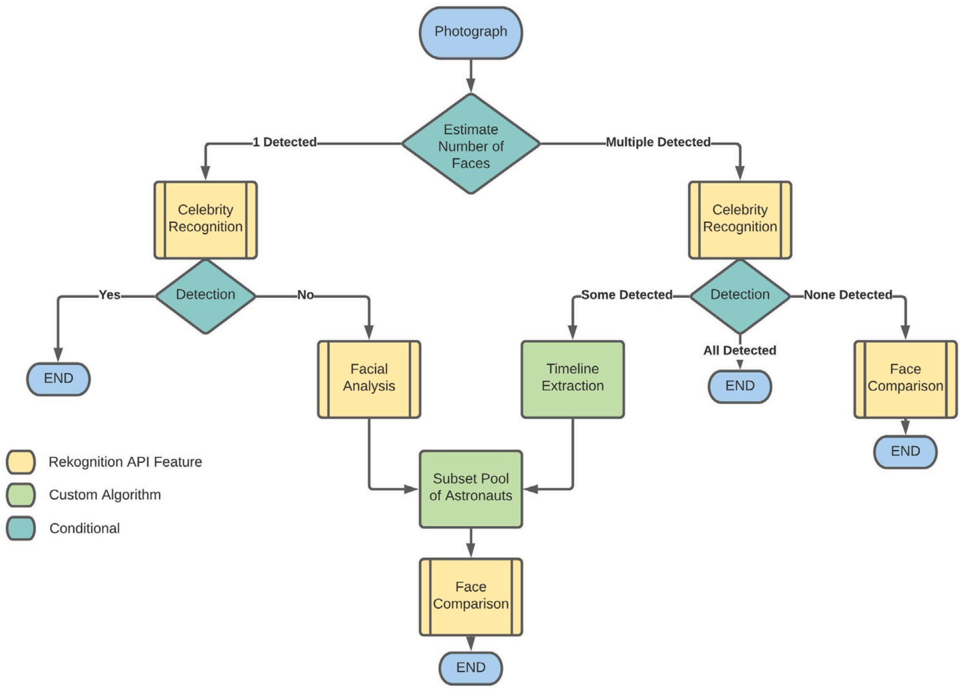

Fig. 3. Overview of the tagging system. The diagram highlights how the Rekognition API features and our algorithms are connected together.

Fig. 4. NASA Johnson. "iss028e032123" 17 Aug 2011. Online image. Flickr. 31 Oct 2021. Astronaut Satoshi Furukawa is highlighted in the background.

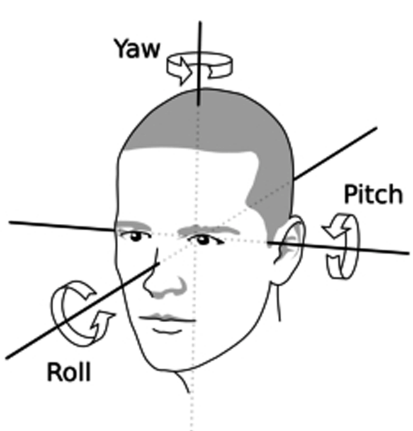

Fig. 5. The yaw, pitch, and roll attributes of a face orientation [36].

are to be analyzed, while keeping their identities protected. Social networks can be generated by giving each entity a generic identifier and graphs can be presented where interactions are clearly shown. As a result, the technique can not only be used to automate tagging processes, but can also be used to create interaction maps that help develop an understanding of the environment, without the need to publicize identities.

4.1. Agency interactions

Identification of astronauts in photographs enables us to determine inter- and intra-agency relationships, and can help us draw tentative conclusions about how astronauts from different agencies interact with each other on board the space station. Fig. 6 shows the interaction between astronauts from different agencies, as photographed across 63 ISS expeditions using the *Flickr captioned photos*. As these photos are procured from a NASA-run Flickr account, almost half of all photos show at least one NASA astronaut. A large percentage of NASA astronauts are photographed with each other, compared to their Roscosmos counterparts. While ESA and JAXA astronauts are occasionally photographed with Russian cosmonauts, a greater proportion of them are photographed with NASA crew members. Interestingly, the interaction between JAXA and ESA astronauts is minimal and most astronauts from smaller agencies are pictured with NASA or Roscosmos astronauts only. Interaction between those agencies are limited to when crews from multiple missions are occupying the space station at the same time. With availability of more photos, from all agencies, we can use the tagging system to further give weight to the inter-agency interactions. Identification of modules, seen in the background, would also enable us to understand the nature of these interactions.

4.2. Astronaut networks

With the availability of *unpublished photos* from the first seventeen expeditions, we can use the tagging system to identify astronauts in those photos and pair that data with the identification analysis done on the counterpart Flickr photos for those expeditions. This allows us to build a more comprehensive visualization of the network of interactions

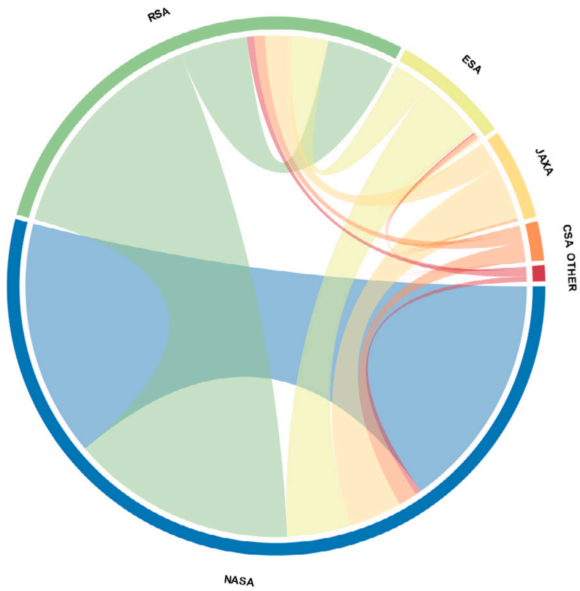

Fig. 6. Interactions between agencies across 63 expeditions using photographs published on NASA Johnson Space Center Flickr account.

between astronauts. If NASA has a criteria for which photographs are made public, then the inclusion of the *unpublished photos* in our analyses minimizes any selection bias. To understand the astronaut interactions, we combined the data of astronauts identified in *Flickr captioned photos* and *unpublished photos* and converted it into a paired array. This array detailed which two astronauts were photographed together, as well as the frequency of their interactions. We excluded all astronauts from the data that had not been on board the space station for more than fourteen days. Missions to ISS involve docking of the spacecraft to the space station for a small period of time. Some crew members remain in the spacecraft and have very limited interactions with other astronauts. Excluding their information from the data allows us to focus on crew members that reside in the space station for a longer period of time, where their interactions are more meaningful.

Using R statistical language [37], we generated a network graph that shows the interactions of all astronauts on board the space station, during the first seventeen ISS expeditions, using both photo sets (Fig. 7). Each node represents an astronaut with a color assigned for their agency. An edge represents two astronauts being photographed together, the size of which depends upon how many of such interactions exist. We use the Fruchterman–Reingold algorithm [38] for the graph drawing, ensuring the fewest number of overlaps between edges for an aesthetically pleasing and analytically useful graph.

The first six expeditions had three crew members each, with NASA and Roscosmos alternating with a 2:1 crew pattern. The next six expeditions, following the loss of the Space Shuttle Columbia in February 2003, saw two astronauts paired together, one from each agency. During Expedition 13, an additional astronaut from outside NASA or Roscosmos was included for a long term stay on board the space station. After that, the size of mission crews increased as well as the variability of when each member traveled to the space station for an expedition [39].

The network graph shows strong relationships between members of the same expedition, from the thickness of the edges between two and three astronaut groups. The thinner lines mostly represent photographs taken during a crew changeover. During the first expeditions, members of a new expedition inhabited the space station alongside the departing crew for a week or two. For the later missions, crew flights were staggered and members spent more time with crew from preceding or succeeding expeditions on board the space station. The thin edges in the network graph represent these interactions that members from different expeditions might have with each other. The graph is connected, meaning that two astronauts, through a series of other astronauts, can be joined with each other.

Fig. 8 shows a network graph mapped on a circle to further illustrate the interactions between the long-duration-stay astronauts. The graph was created using both photo sets from the first twelve expeditions, when crew flights were not staggered; that is, crew from the same mission arrived at the space station together. Except for the instances where astronauts were part of two different expeditions, the interactions are high between crew of the same expedition and low between crew of two different expeditions. In these photos, an astronaut was seen with another astronaut of the same crew 64% of the time. Most interactions with members of a different crew happened during the changing of the occupants, across a seven- to twelve-day period, a fact that is highlighted by the thin edges between adjacent expeditions in the network graph.

The most photographed day, identified using the EXIF data of the Flickr photos, was February 19, 2010, when 13 astronauts were on board the space station, during the handover between the crew of expeditions 22 and 23. Of the 39 photos taken that day inside the ISS, most were group photos between members of the two expeditions taken in the space shuttle and the space station. It has become tradition that members of the current crew are waiting at the hatch connected to an arriving vehicle, welcoming the new crew, who themselves become the welcoming group for the next expedition.

Beginning with Expedition 13, crew arrival to the space station was staggered. For each expedition from 13 to 17, one astronaut would arrive at the space station by themselves on a Space Shuttle (excluding the members of the shuttle flight crew), and would be added to the next expedition. Now for the first time, an astronaut interacted with two different crews while on board the space station. Fig. 9 presents a circular network graph for expeditions 13 through 17, with nodes representing astronauts with alternating colors to represent different expeditions. Members who arrived at the space station after their fellow expedition members, and were subsequently transferred to the next expedition, are highlighted in red. While these astronauts spent a significant number of days with members of two expeditions, their recorded interactions were unequally distributed: they were photographed 65% of the time with the crew that was already on board the space station when they arrived. The graph clearly shows this phenomenon with thicker connections between the red nodes and the members of their first expedition (the nodes preceding them). Being welcomed to the space station and then becoming the welcoming party to a new crew, as is tradition, was not enough to normalize their interaction frequency. We can only hypothesize that perhaps focus on major work conducted in partnership with other crew members when an astronaut first arrives at the space station is high as new ISS inhabitants adjust to life in space, and that the interactions dwindle, perhaps due to working more independently as they gain more experience and get closer to leaving the space station. For example, scenes in the film *Space Explorers: The ISS Experience*, made on ISS during Expeditions 58 and 59, show NASA astronaut Anne McClain giving an orientation tour of the station's facilities and both describing and showing how to position one's body while working in microgravity to her colleague Christina Koch soon after Koch's arrival on board [1]. Availability of unpublished photos from the later expeditions will help address this hypothesis as well.

These are just two of many analyses that can be conducted using tagged photographs of astronauts on board the International Space Station. These photographs are the only visual source of determining and understanding the cultures on the space station. By analyzing the frequency of interactions between astronauts, one can hypothesize the type of collective work astronauts do, who they work with most, and what agencies do to promote inter-agency interactions.

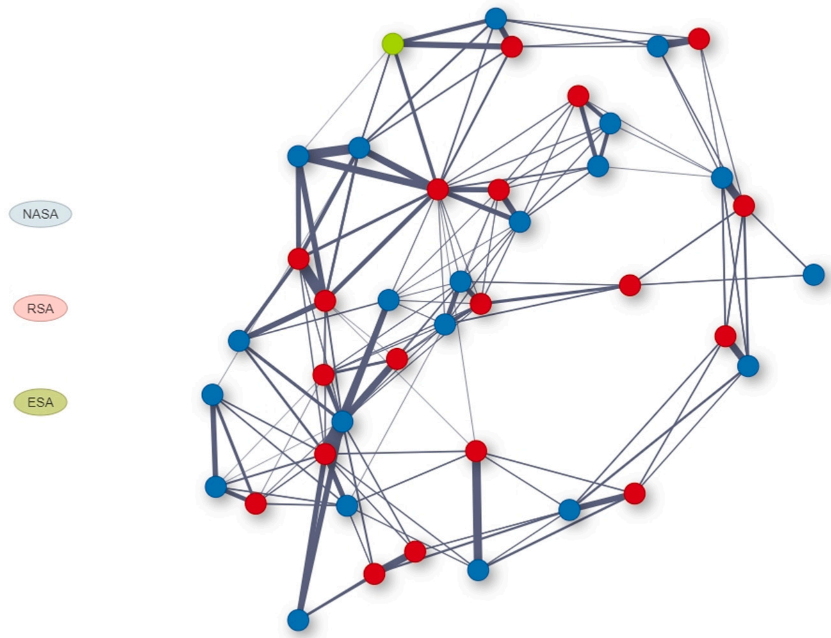

Fig. 7. Network of astronauts photographed on board the space station between Expedition 1 and 17. Nodes represent an astronaut given a color based on their agency, and edges represent frequency of two astronauts photographed together. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

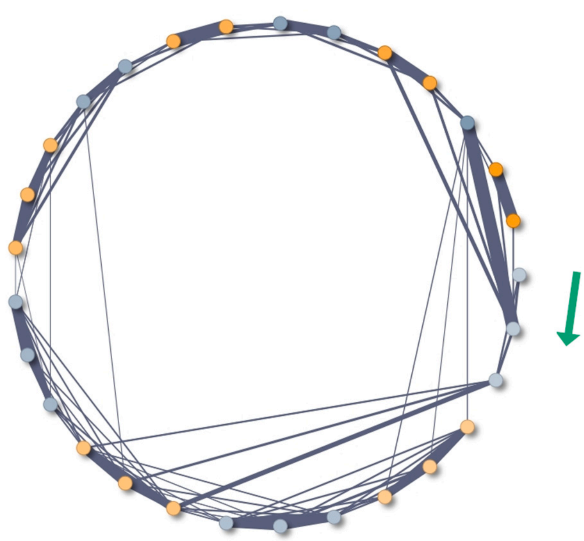

Fig. 8. Circular network graph of long-duration astronauts as nodes from Expeditions 1 through 12. Alternating color palette is used to represent crew from different expeditions. Edges denote frequency of photos taken between 2 astronauts. Arrow indicates beginning of chronological order of expeditions starting with Expedition 1. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

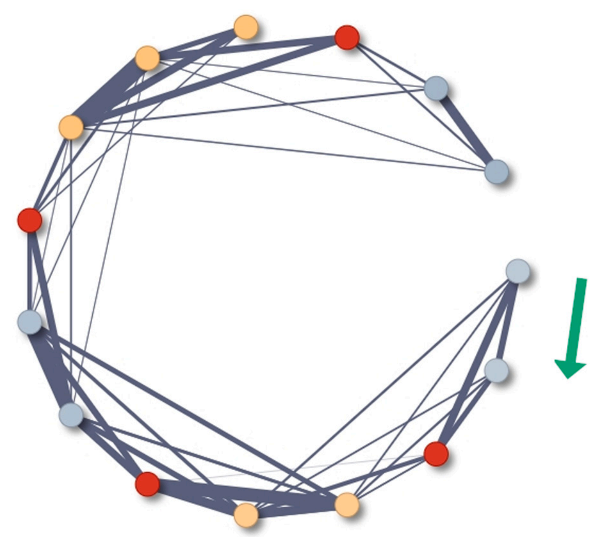

Fig. 9. Circular network graph of astronauts as nodes from Expeditions 13 through 17. Alternating color palette is used to represent crew from different expeditions. Edges denote frequency of photos taken between 2 astronauts. Astronauts who arrived separately to the space station and were transferred to the next expedition are represented as red nodes. Arrow indicates beginning of chronological order of expeditions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5. Limitations

There are obvious limitations in using an image dataset in this way, as it is a highly curated proxy for actual behavior. However, there are no other accessible data sources which would enable a social analysis of this kind and, lacking the methods developed here, NASA has not utilized the image set to understand social relations on board the ISS. While some of our preliminary conclusions using this analysis may be predictable, they have never been demonstrated previously. Taking the limitations into account, our results indicate that the spatial separation between the Russian Orbital Segment (modules Zarya, Zvezda, Poisk, Rassvet in those time periods) and the US Orbital Segment (modules Unity, Harmony, Tranquility, Destiny, Leonardo, and including the ESA Columbus, and the JAXA Kibo), continues into and is reinforced by social separation in crew interactions (Fig. 6). Despite the ideals of international cooperation, national and agency affiliations are still a major structuring influence on the creation of a space society.

There are also differences between Expeditions 1–12, when crews were replaced at the same time, and Expeditions 13–17, when they were staggered (Figs. 8–9). Unsurprisingly perhaps, people form stronger social bonds through shared experiences, such as the training for a particular expedition and the journey to the ISS. However, with the introduction of staggered crew scheduling, expedition crews socialized as much between crews as within them. Underlying our interpretation of these results is the assumption that a greater intensity of interactions indicates sympathy and cooperation rather than indifference or interpersonal conflict; and that the former situation has better results in terms of productivity. These data provide an evidence base for future space habitat planning.

In traditional archaeological studies, social relations must often be inferred from material context alone. An advantage of the archaeology of the contemporary past is the ability to draw on the documentary record, oral history, and digital data and techniques. The use of machine learning applied to NASA's photographic archives has illuminated aspects of crew interactions on board a distinctive space habitat, as well as developing a procedure for future investigations of the International Space Station.

6. Conclusion

In this study we present a tagging system that leverages the Amazon Rekognition API to automatically tag astronauts photographed in photos taken on board the International Space Station. The tagging system is made efficient by generating pools of possible matches through the use of gender identification and ISS travel history. Our system shows significant accuracy on unpublished photos provided by NASA and can be put in place to automatically tag photos as they arrive from the space station. We also present some use cases of the tagging and generate network graphs that show interactions between astronauts from different agencies and expeditions. Such analyses were not possible before. Unpublished photos from later expeditions, and from different agencies and sources, can be efficiently parsed to gain more insight into life on the space station as well as the social norms and interactions on ISS.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Felix, P. Studios, Space explorers: The ISS experience, 2019.

[2] J.E. Catchpole, The International Space Station: Building for the Future, Springer Science & Business Media, 2008.

[3] Space Foundation, Space Briefing Book: Space Stations, 2021, https://www.spacefoundation.org/space_brief/space-stations/, (Accessed 17 October 2021).

[4] Nature, Astronauts have conducted nearly 3000 science experiments aboard the ISS, 2020, https://www.nature.com/articles/d41586-020-03085-8, (Accessed 17 October 2021).

[5] NASA, International Space Station Facts and Figures, 2021, https://www.nasa.gov/feature/facts-and-figures, (Accessed 17 October 2021).

[6] NASA, NASA space flight human-system standard volume 1, Revision A: Crew health, 2007, https://standards.nasa.gov/standard/nasa/nasa-std-3001-vol-1, (Accessed 17 October 2021).

[7] W. Salmond, J. Walsh, A. Gorman, Eternity in low earth orbit: icons on the international space station, Religions 11 (11) (2020) 611.

[8] J.S.P. Walsh, A.C. Gorman, A method for space archaeology research: the international space station archaeological project, Antiquity 95 (383) (2021) 1331–1343.

[9] J.S.P. Walsh, A.C. Gorman, P.C. no, Postorbital discard and chain of custody: the processing of artifacts returning to earth from the international space station, Acta Astronautica (ISSN: 0094-5765) 195 (2022) 513–531, http://dx.doi.org/10.1016/j.actaastro.2022.03.035, https://www.sciencedirect.com/science/article/pii/S0094576522001448.

[10] J.S.P. Walsh, A.C. Gorman, W. Salmond, Visual displays in space station culture: an archaeological analysis, Current Anthropology 62 (6) (2021) 804–818.

[11] CAA, CAA and CAA history, 2021, https://caa-international.org/about/history/, (Accessed 29 November 2021).

[12] S. Olsen, A. Brickman, Y. Cai, Discovery by reconstruction: exploring digital archeology, in: SIGCHI Workshop (Ambient Intelligence for Scientific Discovery), AISD, 2004.

[13] B.A. Saidel, G.L. Christopherson, Four days at Khalasa: using aerial photography and GIS analysis to reappraise Woolley and Lawrence's survey of Byzantine Elusa in the Western Negev Desert, Palest. Explor. Q. 137 (1) (2005) 53–63.

[14] C. Cox, Satellite imagery, aerial photography and wetland archaeology: An interim report on an application of remote sensing to wetland archaeology: The pilot study in Cumbria, England, World Archaeol. 24 (2) (1992) 249–267.

[15] G. Guidi, M. Russo, S. Ercoli, F. Remondino, A. Rizzi, F. Menna, A multi-resolution methodology for the 3D modeling of large and complex archeological areas, Int. J. Architect. Comput. 7 (1) (2009) 39–55.

[16] F. Di Salvo, M.L. Brutto, Full-waveform terrestrial laser scanning for extracting a high-resolution 3D topographic model: A case study on an area of archaeological significance, Eur. J. Remote Sens. 47 (1) (2014) 307–327.

[17] C. Engel, P. Mangiafico, J. Issavi, D. Lukas, Computer vision and image recognition in archaeology, in: Proceedings of the Conference on Artificial Intelligence for Data Discovery and Reuse, 2019, pp. 1–4.

[18] O.I. Abiodun, A. Jantan, A.E. Omolara, K.V. Dada, N.A. Mohamed, H. Arshad, State-of-the-art in artificial neural network applications: A survey, Heliyon 4 (11) (2018) e00938.

[19] Twitter, International Space Station, 2021, https://twitter.com/Space_Station, (Accessed 17 October 2021).

[20] Instagram, International Space Station, 2021, https://www.instagram.com/iss/, (Accessed 17 October 2021).

[21] Flickr, NASA Johnson, 2021, https://www.flickr.com/photos/nasa2explore, (Accessed 17 October 2021).

[22] A. Stoken, Personal communication, 2022.

[23] K. Arnold, J. Gosling, D. Holmes, The Java Programming Language, Addison Wesley Professional, 2005.

[24] B. Zhao, Web scraping, in: Encyclopedia of Big Data, Springer, 2017, pp. 1–3.

[25] Flickr, API, 2021, https://www.flickr.com/services/api/, (Accessed 29 October 2021).

[26] Flickr, NASA Johnson (iss026e028062), 2021, https://www.flickr.com/photos/nasa2explore/9466773724/, (Accessed 17 October 2021).

[27] G.G. Chrysos, S. Moschoglou, G. Bouritsas, Y. Panagakis, J. Deng, S. Zafeiriou, P-nets: Deep polynomial neural networks, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 7325–7335.

[28] K. Smelyakov, A. Chupryna, O. Bohomolov, I. Ruban, The neural network technologies effectiveness for face detection, in: 2020 IEEE Third International Conference on Data Stream Mining & Processing, DSMP, IEEE, 2020, pp. 201–205.

[29] D.E. Rumelhart, R. Durbin, R. Golden, Y. Chauvin, Backpropagation: The basic theory, in: Backpropagation: Theory, Architectures and Applications, Lawrence Erlbaum Hillsdale, NJ, USA, 1995, pp. 1–34.

[30] C. Tan, F. Sun, T. Kong, W. Zhang, C. Yang, C. Liu, A survey on deep transfer learning, in: International Conference on Artificial Neural Networks, Springer, 2018, pp. 270–279.

[31] X. Yin, X. Liu, Multi-task convolutional neural network for pose-invariant face recognition, IEEE Trans. Image Process. 27 (2) (2017) 964–975.

[32] Amazon, Amazon rekognition, 2021, https://aws.amazon.com/rekognition/, (Accessed 31 October 2021).

[33] NASA, Visitors to the station by country, 2021, https://www.nasa.gov/feature/visitors-to-the-station-by-country/, (Accessed 31 October 2021).

[34] J. Buolamwini, T. Gebru, Gender shades: Intersectional accuracy disparities in commercial gender classification, in: Conference on Fairness, Accountability and Transparency, PMLR, 2018, pp. 77–91.

[35] Flickr, NASA Johnson (iss028e032123), 2021, https://www.flickr.com/photos/nasa2explore/9498010418, (Accessed 31 October 2021).

[36] T. Jantunen, J. Mesch, A. Puupponen, J. Laaksonen, On the rhythm of head movements in finnish and Swedish sign language sentences, in: Speech Prosody 8, Boston, USA, May 31–June 3, 2016, The International Speech Communication Association (ISCA), 2016, pp. 850–853.

[37] R.C. Team, et al., R: A Language and Environment for Statistical Computing, Vienna, Austria, 2013.

[38] T.M. Fruchterman, E.M. Reingold, Graph drawing by force-directed placement, Softw. - Pract. Exp. 21 (11) (1991) 1129–1164.

[39] SpaceFacts, Welcome to the mission reports of the ISS resident crews, 2021, http://www.spacefacts.de/english/iss.htm, (Accessed 31 October 2021).