A Comprehensive Database for Benchmarking Imaging Systems

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Abstract—Cross-modality face recognition is an emerging topic due to the wide-spread usage of different sensors in day-to-day life applications. The development of face recognition systems relies greatly on existing databases for evaluation and obtaining training examples for data-hungry machine learning algorithms. However, currently, there is no publicly available face database that includes more than two modalities for the same subject. In this work, we introduce the Tufts Face Database that includes images acquired in various modalities: photograph images, thermal images, near infrared images, a recorded video, a computerized facial sketch, and 3D images of each volunteer's face. An Institutional Research Board protocol was obtained and images were collected from students, staff, faculty, and their family members at Tufts University. The database includes over 10,000 images from 113 individuals from more than 15 different countries, various gender identities, ages, and ethnic backgrounds. The contributions of this work are: 1) Detailed description of the content and acquisition procedure for images in the Tufts Face Database; 2) The Tufts Face Database is publicly available to researchers worldwide, which will allow assessment and creation of more robust, consistent, and adaptable recognition algorithms; 3) A comprehensive, up-to-date review on face recognition systems and face datasets.

Index Terms—The tufts face database, computerized face sketches, thermal, 3D, near infrared, face recognition, cross-modality

1 Introduction

Algorithms performing autonomous facial recognition have many profound implications in the fields of homeland security, human trafficking, law enforcement, biometric identification, and multimedia [1], [2], [3], [4]. Extensive research on the topic has led to critical developments in the area [5], [6] yet the field continues facing difficulties with heterogeneous face recognition (HFR) algorithms: matching face images across different image types, such as thermal, near-infrared (NIR), 2D, 3D, and other modalities (See Fig. 1). Often times, the motivation behind HFR is there is only one modality of face images can be acquired as probe images [7]. For instance, face sketches of a criminal are sometimes the only evidence in law enforcement applications [8]. Accurate cross-modality face matching is necessary due to the increasing variety of imaging sensors in different real-life scenarios, such as depth, optical, capacitive, and thermal: for example, night vision cameras can provide more information in low/no light military applications. Furthermore, researchers developing facial recognition systems are adopting multi-modal information to overcome the obstacles to achieve a higher accuracy. It has been shown that the combination of multiple imaging sensor information, such as $2D + 3D$, can significantly improve facial recognition rate [9].

Such cross-modality matching algorithms need to be extensively tested and validated in order to ensure their robustness in recognizing faces across images from advanced sensors and traditional surveillance cameras [10]. Therefore, it is crucial to provide researchers with the ground truth images to benchmark their recognition algorithms and aid in the development of potential solutions to the existing HFR challenges.

Currently, there is no publicly available multi-modality face database that includes visible, near-infrared, thermal, computerized sketch, video and 3D images. Researchers are limited to test their algorithms on very narrowly constrained test samples for one or two modalities. The Tufts Face Database, the most comprehensive multi-modality face database published to date, addresses this issue as it includes six different types of image modalities: photographic images, a computerized facial sketch created from a volunteer's portrait using the FACEs software, thermal images, near infrared (NIR) images, a video, and 3D images of the participant. This database will provide researchers

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Fig. 1. Heterogeneous face recognition in real-life scenarios: images captured through different sources, such as (a) social media; (b) driver's licenses, passports, and other identification documents; (c) night-vision surveillance cameras; (d) Thermal cameras; and (e) 3D cameras.

developing new recognition algorithms with a dataset to use as a benchmark to validate performance and accuracy.

An Institutional Research Board protocol was developed, and more than 10,000 raw images were collected from 113 volunteers of different nationalities, gender identities, ages, and ethnicity at Tufts University.

The paper presents the following:

- An up-to-date review of existing facial recognition algorithms and systems.
- A comparative summary of publicly available face datasets.
- Information on the Tufts Face Database, a comprehensive face database, which contains face images captured in multiple modalities.

The modalities include different variations of 2D face photographs, computerized facial sketches, thermal face photos, near infrared face images, a recorded video, and 3D face images. All 6 modalities are available for every one of 113 individuals depicted in the database. This database will be available to researchers worldwide in order to benchmark facial recognition algorithms for sketch, thermal, NIR, 3D face recognition and heterogamous face recognition.

This paper is organized as follows. Section 2 presents a brief review of the literature and related work. In Section 3, the acquisition procedure of the Tufts Face Database is described. Then, the instructions for accessing the database are outlined in Section 4. Finally, Section 5 summarizes the contributions of this work and discusses the future directions.

2 Related Work

This section outlines different types of recognition systems currently in use, their existing challenges and forthcoming advances, as well as a comparison of the Tufts Face Database to other existing databases.

2.1 Different Types of Face Recognition Systems, Their Development, and Applications

Conventional visible face recognition systems have been used in a broad range of real-life applications in fields such as law enforcement, homeland security, biometric identification, cognitive psychology, and entertainment [11]. Generally, an automatic real-time facial recognition system comprises of two steps [12]: face detection and face recognition. Despite extensive work done in the field [13], automated facial recognition systems still lack in accuracy when compared to human performance [14], [15]. The existing challenges for an automated facial recognition system include: uncontrolled conditions caused by low-quality surveillance cameras or sensors, unpredictable environments, difficulty in detecting faces in video content, emulating the effects of aging, low tolerance to the variation in facial expressions, illumination changes [16], and the difference in body positions [14].

Sketch-to-face recognition is a commonly used method to assist police to identify persons of interest, such as suspects or missing persons, especially when there is limited access to other evidence [17], [18]. Usually there are two types of sketches: hand-drawing sketches and computerized sketches, both based on an eyewitness' testimony. Most law enforcement agencies are adopting computerized sketches to identify criminals due to its cost efficiency over hand-drawn sketches [19]. The existing challenges of a sketch-to-face recognition system include: significant differences in shape and textures across modalities, and limited amount of testing and training data. Methods such as component-based MLBP, holistic SIFT feature descriptors, and Log-Gabor filtering were utilized and tested to perform promising computerized sketch-to-face recognition [20], [21], [22], [23]. Moreover, intra-modality and inter-modality algorithms for face-sketch recognition can be fused together to yield better performance [24]. Sketch photo synthesis methods [25] were introduced to improve the recognition accuracy of computerized sketch-to-face recognition by reducing the discrepancies between real facial photos and computerized sketches. Most recently, deep learning algorithms, such as DCNN [26], are being developed for face photo-sketch recognition, where the neural network is fine-tuned by using transfer learning and traditional data augmentation methods.

Thermal face recognition is widely used in biomedical applications. This type of image contains reliable and distinguishable physiological biometric features [27], [28]. The amount of radiation emitted by an object increases with temperature; therefore, thermography depicts variations in temperature. When viewed through a thermal imaging camera, warm objects stand out well against cooler backgrounds; humans become easily visible against the environment, regardless of environmental illumination. As a result, facial thermography is particularly useful to first responders during calamities and in military applications. However, thermal imaging technology has several drawbacks in the context of autonomous facial recognition system. The infrared face images displays the body heat pattern, which can be easily affected by ambient temperature, air flow conditions, exercise, illness, and drugs [29]. Also, thermal face images provide less facial features when compared to visible face images. Currently, feature extraction algorithms such as gray-scale value histogram features [30], thermal local binary pattern (LBP), SIFT features [31], and speeded up robust features (SURF) [32], [33], are widely applied in thermal face recognition. Image transformations, such as wavelet transform [34] and Gabor filtering [35], were used to enhance the robustness of extracting face appearance features. Meanwhile, in order to match the thermal face image to the visible face image, algorithms such as partial least squares-discriminant analysis (PLS-DA) [36], [37] that reduce the modality gap were proposed. Furthermore, leading machine learning techniques and classifiers were applied to construct thermal face recognition systems [7], [38]. Machine learning methods such as the Optimized super-pixel and AdaBoost classifier were combined for human thermal face recognition [39]; Generative Adversarial Network (GAN) based method [40] was developed to address challenges like

TABLE 1
Advantages and Limitations of Popular Imaging Sensors

Characteristics	Thermal/Near infrared	3D	Visible
Visibility in low/no light	yes	yes	no
Record image through translucent obstacles	yes	no	no
Provide color content information	no	yes	yes
Display surface temperatures of solid objects	yes	no	no
Distinguish objects at varying distances	no	yes	yes
Image quality	low	low	high
Presence of noise	low	low	high
Commercial cost	high	high	low
Consumer applications	limited	limited	yes
Existing tools for facial recognition	limited	limited	more

occlusions, different skin tones and limited thermal training data available for face recognition.

Near-infrared (NIR) face recognition systems were proposed to overcome the challenges of no illumination and varying pose [41]. Imaging beyond the visible spectrum has recently received a lot attention from the research community [42] as opens a new way for face detection, localization and recognition [43], [44]. Proper feature descriptors and classifiers are found in literature for visible (VIS)-to-NIR face recognition. Wasserstein convolutional neural network (WCNN) approach was proposed to learn invariant features between NIR and VIS face images [45]. Liao et al. [46] combined the difference of Gaussian (DoG) filter and multi-block local binary pattern (MBLBP) to represent face features. In [47], HoG and LBP descriptors were utilized to explore the accuracy of VIS-to-NIR face recognition system. Furthermore, a multi-view smooth discriminant analysis was proposed to learn a common discriminative feature space for matching visible and NIR face images [48]. Canonical correlation analysis estimated the similarity between NIR and VIS images by training on NIR/VIS image pairs of the same individual [49]. Chen et al. [50] converted NIR images to synthetic VIS images for matching by using local linear embedding with a dictionary of corresponding NIR/VIS face pairs. Handling cross-spectral face images is still an open research topic.

3D face recognition systems have seen a large spike in interest in the past few years. A 3D scanner can capture the surface texture and the depth information. 3D scanners can generate higher image quality with distortion-free images, can capture partial scans more effectively as they have potential for better description of facial features enable creation of synthetic face images, and are invariant to the point of view [51]. Most importantly, the depth information from a 3D image can be combined with 2D features to deliver higher recognition rates [51]. As 3D technology becomes more prevalent and affordable, the demand for real world applications such as 3D image reconstruction algorithms and 3D face recognition continue gaining more attention [52], [53], [54]. Moreover, 3D scanners have recently been recommended to address the challenges of 2D recognition systems [55]. In recent years, several 3D acquisition algorithms have been developed, among them structured light, stereo, and structure from motion. Structure from Motion (SfM) is a more practical approach for facial 3D reconstruction in a real-world environment as this algorithm constructs a 3D image from a sequence of images taken from different perspectives. As such, a 3D image of an individual can be reconstructed from multiple surveillance camera images. Surface registration-based and feature matching-based approaches are the two main categories in 3D face recognition. The surface registration-based approaches commonly use natural or variant Iterative Closest Point (ICP) algorithms [56]. Feature matching-based approaches match two 3D facial surfaces defined in different coordinate systems based on object-centric shape features. In the literature there are several methods for performing 3D face recognition. Medioni and Waupotitsch [57] performed 3D face recognition using iterative closest point algorithm for matching surface of the 3D face. Lao et al. [58] used 2D edges and iso-luminance contours to locate irises. Features are determined using the location of the iris as a reference point, enabling subsequent face standardization is performed. Chang et al. [59] used principal component analysis based recognition using a combination of 3D and 2D images. The experiment resulted in 99 percent accuracy for $3D + 2D$ modality and 94 and 89 percent for 3D and 2D alone, respectively.

Heterogonous face recognition (HFR) matches face images across different image types. As diverse imaging sensors are widely used in practical applications, heterogonous face recognition is now attracting growing attentions in both research and industry community. For instance, face recognition using thermal camera, near infrared camera and 3D depth camera emerged in literature as new modalities addressing issues of complicated light conditions, biometric identification, and military applications [60]. Furthermore, the law enforcement's reliance on computerized face sketches in the absence of photographic information results in a growing need for such modalities to be included in HFR approaches. The advances in image collection and widespread reliance on different sensors is the root of HFR's growing importance within both research and industry. Table 1 summarizes the advantages and limitations of popular imaging sensors, such as thermal/near infrared cameras, 3D camera, and visible light cameras.

Research continues facing difficulties that arise from the modality gaps between heterogeneous face images. Conventional approaches can be categorized as synthesis based methods [61], [62], [63], [64], [65], common space projection based methods [66], [67], [68], [49], [69], and feature descriptor based methods [7], [70]. Furthermore, a graphical representation based HFR method (G-HFR) was described in [71]. More works can be found in [7], [10], [72], [73], [74].

2.2 Existing Databases Summary and Comparison

Significant efforts have been put into building face databases to satisfy the basic needs of fast development of facial recognition research and applications. Table 2 provides a brief overview of the most popular databases built for researchers to evaluate facial recognition algorithms, as well as providing sufficient amount of training data for machine learning algorithms.

2D face databases are used in most face recognition research topics. The FERET [75], [76] database was a pioneering large-scale color database built in the late 90s. FRVT (Face Recognition Vendor Test) 2000 [77] and 2002 [78]

TABLE 2
A Comparison of Popular Face Datasets

Database Name & References	2D	Thermal	NIR	CS	3D	#people	Highlights
10k US Adult Faces Database [105]	✓					≈10,168	Natural face photographs and several measures for 2,222 of the faces.
The AR Face Database [81]	✓					126	Color face images with different expressions, illumination conditions, and add-ons accessories like sunglasses and scarves.
Yale Database [83]	✓					15	165 grayscale images in GIF format.
AT&T Database [81]	✓					40	10 different images (time, lighting, expression, glasses) of each person
Caltech Faces [88]	✓					27	450 frontal face images.
CAS-PEAL Face Database [89]	✓					1040	A large-scale Chinese face database
The CMU Multi-PIE Face Database [80]	✓					337	Improve version of PIE face database; images were captured under 15 view points and 19 illumination conditions.
Cohn-Kanade AU Coded Facial Expression Database [106]	✓					100	Given emotion labels for different facial expressions.
The Color FERET Database [75]	✓					1199	Large-scale, one of the face database pioneer work.
Indian Movie Face database [107]	✓					100	34512 images of Indian actors
Japanese Female Facial Expression (JAFFE) Database [90]	✓					10	7 facial expressions (6 basic facial expressions + 1 neutral) depicting 10 Japanese female subjects.
Karolinska Directed Emotional Faces (KDEF) [108]	✓					70	Suitable for perception, attention, emotion, memory and backward masking studied
Labeled Faces in the Wild [109]	✓					5749	13,000 images of faces collected from the web
NIST Mugshot Identification Database [110]	✓					1573	Large scale mugshots face images with front and side view.
PUT Face Database [111]	✓					100	High resolution images with pose variations and expression
Natural Visible and Infrared Facial Expression (USTC-NVIE) [102]	✓	✓				100	Visible and infrared facial expression database
IRIS Thermal/Visible Face Database [104]	✓	✓				30	Visible and thermal face images with expression, pose, and illumination
The Terravic Facial Infrared Database [112]		✓				20	Thermal face images for 20 people with accessories
The Hong Kong Polytechnic University NIR Face Database [113]			✓			350	Large scale NIR face database from
CASIA NIR-VIS 2.0 database [114]	✓		✓			725	Pairs of visible (VIS) and NIR images
Long Distance Heterogeneous Face Database (LDHF-DB) [115]	✓		✓			100	Visible (VIS) and near-infrared (NIR) face images at distances of 60m, 100m, and 150m outdoors and a 1m distance indoors.
The PRIP Viewed Software-Generated Composite (PRIP-VSGC) database [20], [21]				✓		123	Computerized sketch build based on 123 participants from the AR face database
The UoM-SGFS database [101]				✓		600	A composite sketch dataset based on FERET dataset
3D Mask Attack Database (3DMAD) [116]	✓				✓	17	76500 frames covering 17 people under controlled conditions, frontal view and neutral expression
3D_RMA database [117]					✓	120	Created with a 3D acquisition system using structured light.
The Basel Face Model (BFM) [118]					✓	200	Uses registered 3D scans of 100 male and 100 female faces
Binghamton University Facial Expression Database (BU-3DFE/BU-4DFE) [119]	✓				✓	100	The database has large age range, nationality diversity; high-resolution 3D dynamic facial expression database
The Bosphorus Database [120]	✓				✓	105	For 2D/3D face recognition and 3D face reconstruction
The Extended M2VTS Database [86]	✓				✓	295	32 KHz 16-bit sound files, video sequences or as a 3d Model
Texas 3D Face Recognition Database (Texas 3DFRD) [121]					✓	105	Facial color and range images of 105 adults
The EURECOM Kinect Face Dataset [122]					✓	52	A Kinect database of images from 52 people of different facial expressions/different lighting/occlusion conditions
The University of Milano Bicocca 3D face database [123]	✓				✓	143	2D/3D images from 98 males, 45 females; a pair of male twins and a baby included)
The Tufts Face Database	✓	✓	✓	✓	✓	113	The most comprehensive, large-scale (over 10,000 images, 74 females + 39 males, from more than 15 countries with an age range between 4 to 70 years old) face dataset that contains 6 image modalities: visible, near-infrared, thermal, computerized sketch, a recorded video, and 3D images.

challenges furthermore improved the face recognition system evaluation protocols and databases construction to meet real-world applications, which overall provide images for 37,437 individuals. CMU PIE [79] collected by Carnegie Mellon University consists of over 40,000 facial images of 68 people and is one of the most widely used face database for evaluation of pose and illumination variations. Eight years later, Multi-PIE [80] database improved upon the CMU PIE database in a number of categories, increasing the number of participants and facial expression variations. During 90's the development face databases were populated, such as the AR face database [81] (1998, Purdue University), the ORL [81] also known as the ATT database (1994, Cambridge University), MIT face database [82] (1991, Massachusetts Institute of Technology), Yale face database [83] and Yale-B database [84], [85] (1997-2005, Yale University), M2VTS and XM2VTSDB face database [86] (1997, University of Surrey), Georgia Tech face database [87] (1999, Georgia Institute of Technology) and Caltech face database [88] (1999, California Institute of Technology).

Other publicly accessible face databases provide specific test cases for facial recognition for a variety of nationalities, races, and sexes. For example, CAS-PEAL [89] is a large-scale Chinese face database which contains 1040 Chinese participants; The Japanese Female Facial Expression (JAFFE) database [90] contains seven facial expressions posed by 10 Japanese female models; the Indian face database collected frontal face images of 40 south-east asian participants taken in February, 2002 on the IIT Kanpur campus [91]; The Iranian Face Database (IFDB) [92] includes faces of middle-eastern Iranian participants along with information such as volunteers' occupation, skin color, fingerprint, and cosmetic markers (surgical points, fracture or laceration on face). Meanwhile, there are other databases were built for specific practical applications. For instance, SCface (surveillance cameras face database) is an image dataset of uncontrolled indoor environment using surveillance cameras of various qualities; Labeled Faces in the Wild (LFW) [93] is a database of face photographs designed for studying the problem of unconstrained environmental parameters such as position, pose, lighting, expression, background, camera quality, occlusion, age, and gender; YouTube faces database [94] contains 3,425 videos of 1,595 participants designed for studying the problem of unconstrained face recognition in videos; the plastic surgery face database [95] consists of 1800 pre- and post-surgery images depicting 900 participants, which aims to open an new dimension of facial recognition by accounting for surgical interventions and alterations; the Large Age-Gap (LAG) dataset [96] is designed to aid solving the aging problem in facial recognition. The proposed Tufts Database includes a set of pictures with occlusions (such as glasses) and exaggerated facial expressions to allow for robust validation of existing algorithms and would serve as a testbed for development of approaches allowing to minimize the impact of abovementioned noise on recognition accuracy.

Computerized Sketch (CS) face databases have been constructed for evaluation of computerized sketch (CS) to face recognition approaches. Autonomous matching of computerized sketches to face photos is becoming widely studied largely due to the demand from law enforcement agencies. A composite sketch database called The PRIP Viewed Software-Generated Composite (PRIP-VSGC) database was built in [20], [21], which contains computerized sketches for 123 participants based on the images from the AR face database. Extended PRIP (e-PRIP) [97], [98] sketch database was created based on PRIP dataset, further adding a set of composite sketches prepared by an Indian user. The UoM-SGFS database, which is a composite sketch dataset based on the images from the FERET dataset, doubled the number of participants compared to previous work from 2016, now containing 1200 images of 600 participants in 2018 [99], [100], [101]. For composite sketch datasets, photographs of participants were used as references in creating the composite sketches. While there has been a huge spike in interest for computerized sketch to face recognition systems, the availability of robust databases for testing are limited as the sketches are not based on live portrait sittings of the individual. Having a large robust database available where the computerized facial sketches are derived from live portrait sittings of an individual is critical for computerized sketch face recognition system development, validation and testing. The Tufts Face Database is the first large-scale computerized sketch dataset that was created based on live participant sittings.

Infrared thermal images, which record the temperature distribution over faces and the vein branches, are not sensitive to imaging conditions. Thus, thermal face recognition is a powerful technology for biometric identification applications. One of the most commonly used databases is the Natural Visible and Infrared facial Expression Database (USTC-NVIE) [102], which contains both spontaneous and posed expres sions of more than 100 participants, recorded simultaneously by a visible light and an infrared thermal camera. NIST Equinox [103] consists of thermal face images including: co-registered broadband-visible/LWIR(8-12 microns), MWIR(3-5 microns), and SWIR(0.9-1.7 microns); however, it is no longer available online. IRIS [104] provides visible and thermal face image pairs of 30 participants.

Other thermal face images are Carl database [124], [125] Terravic Facial IR Database [112] and Kotani Thermal Facial Emotion (KTFE) [126]. However, availability of thermal image face databases is limited: there is a lower demand for thermal images as compared to 2d databases, and thermal images are significantly more difficult to obtain. The Tufts face database contains a large-scale thermal facial database, with pose variance and facial expression, which provides a benchmark for thermal face recognition research.

A limited number of *NIR face databases* are present in the literature. The CASIA NIR-VIS 2.0 database [114] is the largest face database across NIR and VIS spectrum to date. The PolyU-NIRFD contains images from 350 participants, each contributing about 100 samples with variations of pose, expression, focus, scale, and time [113]. The University of California/Irvine collected a dataset of multispectral images under halogen ambient illumination [44]. The LDHF-DB contains face images collected in an outdoor environment at distances of 60 meters, 100 meters, and 150 meters, with both visible light (VIS) face images captured in daytime and near infrared (NIR) face images captured in nighttime [115].

The cost and time required to capture *3D images* are steadily decreasing, hence researchers have attempted to develop face recognition problems directly on a 3D face

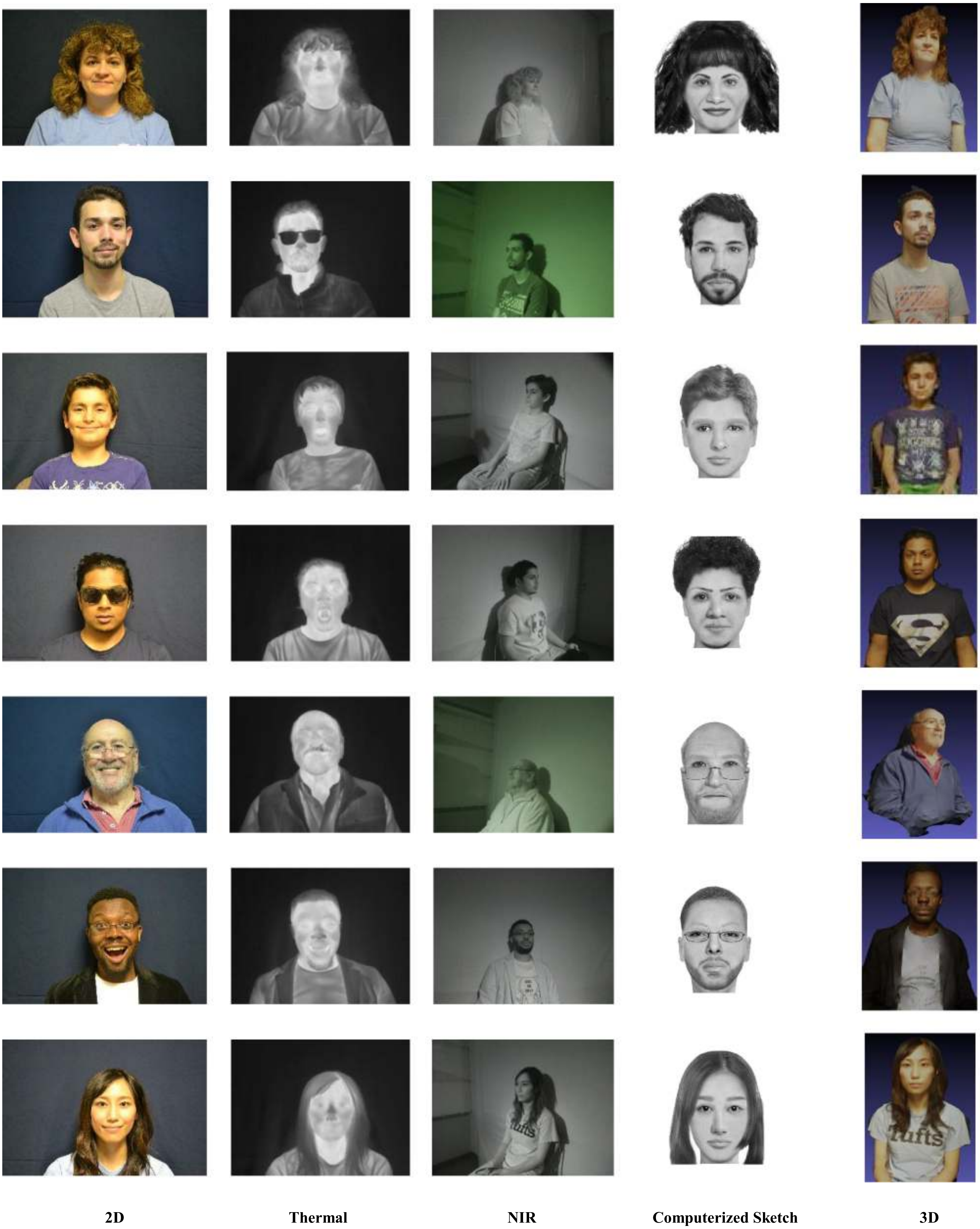
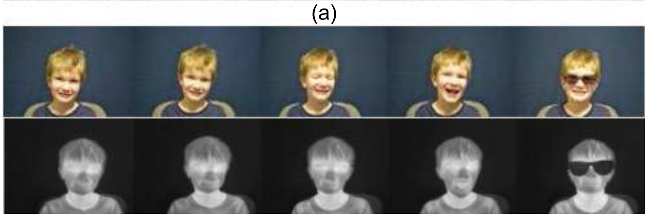


Fig. 2. Example images selected from the Tufts face database. The Tufts database has a wide range of nationalities, ages, and ethnic backgrounds.

model [127]. Part of the face recognition grand challenge (FRGC) [109] offers measures to evaluate the performance of 3D face recognition, which is one of the pioneering works on 3D face datasets. Another early 3D face dataset is 3D RMA [117] face dataset, which was collected by a 3D acquisition system based on structured light with a projector and a camera of low quality and precision, which appears sufficient for prototype testing. MIT-CBCL Face Recognition Database [108] contains synthetic 3D morphable head models of the 10 participants using high resolution 2D images. GavabDB [128] is a 3D face dataset of 61 Caucasian participants built for image applications such as pose correction

(a)



(b)

Fig. 3. (a) and (b) are two sets of frontal images of an individual with the different constraints for both visible and thermal. The images in the first row of each set illustrate visual images of a participant with various facial expressions; and the images in the second row of each set provide corresponding expressions in thermal imaging.

and 3D face model registration. Multimodal database (2D, 2.5D and 3D) FRAV3D Database [129] was captured by specific hardware devices, a Minolta VIVID 700 scanner, developed by researchers focused on RGB-D face recognition. Other well-known and publicly available 3D face databases are BU-3DFE [119], BU-4DFE [130], BP4D [131], Bosphorus [132], Texas 3D Face Recognition Database (Texas 3DFRD) [121], and the EURECOM Kinect Face Dataset (EURECOM KFD) [122]. The Tufts Face Database will provide 3D face images captured by a LYTRO camera, and a 3D face model (a high-quality 3D point cloud reconstructed facial images) for researchers to test and evaluate the robustness of 3D face recognition systems specifically against pose variations. Furthermore, the Tufts Face Database provides the 2D images and a recorded video that were used to generate the 3D face model for researchers who focus of 3D face image reconstruction.

3 The Tufts Face Database Acquisition System

Image acquisition for the Tufts Face Database took place in a 9 $\times$10 ft photographic room. 2D face images were collected from people with different expressions and accessories, under uniformed lighting and constant background conditions. FACEs sketch software was used to develop computerized sketches. Nine camera positions were derived to support the

TABLE 3
Detailed Camera Settings for the Tufts Database

Front face	RGB Thermal	Nikon D3100 FLIR Vue Pro
Around the participant	RGB+ NIR Thermal Mirrorless	QuadCam (self-crafted) FLIR Vue Pro LYTRO ILLUM 40 Megaray Light Field
Video	RGB	QuadCam
Lighting	Visible light NIR light	Diffused light with LED bulbs 850 nm Infrared 96 LED light system

Fig. 4. Selecting facial components using FACES 4.0.

3D face image acquisition and reconstruction. Moreover, a specific thermal and NIR camera systems, temperature settings, and lighting variations were configured for collecting thermal face images. Fig. 2 shows example images selected from the newly proposed Tufts Face Database.

3.1 Existing Databases Summary and Comparison

An institution research board (IRB) protocol was developed in order to collect and publish the Tufts Face Database. The IRB protocol discussed the purpose and procedure of the study, the confidentiality and public access of the database, as well as the protection of participants' identity. Each photographic session took approximately 15 minutes.

The raw image data was collected from 113 volunteers; 100 participant's images were selected and assessed for good image quality.

3.2 Hardware and Software Configuration

Front face camera setting. Acquisition of frontal images was performed using a Nikon D3100 DSLR camera (visual or VIS) and a FLIR Vue pro camera (thermal). The cameras were mounted on tripods and the height of each camera was adjusted manually to correspond to the image center. The distance to the participant was strictly controlled during the acquisition process. A constant lighting condition was maintained using diffused lights. Each participant was asked to pose with (1) a neutral expression, (2) a smile, (3) eyes closed, (4) exaggerated shocked expression, (5) sunglasses. In addition, individuals were instructed to remove any eyewear during frontal thermal acquisition. Fig. 3 shows examples of sets of frontal images of each individual with the different constraints for both visible and thermal.

Each participant was seated in front of a blue background in close proximity to the camera.

Angular acquisition camera settings. Angular acquisition was performed by using 3 different cameras: a LYTRO ILLUM 40 Megaray Light Field Camera, a FLIR Vue Pro camera, and a self-crafted QuadCam (an array of 4 cameras) NIR+RGB device. Each individual was asked to look at a fixed viewpoint while the cameras were moved to 9 equidistant positions forming an approximate semi-circle around the individual. The lighting condition for NIR imaging was maintained by using an 850nm Infrared 96 LED light system. The 3D models were reconstructed using open-source structure-from-motion algorithms. Table 3 below demonstrates the detailed camera settings.

Computerized facial sketches. were generated using software FACES 4.0 [70], one of the most widely used software packages by law enforcement agencies, the FBI, and the US Military. The software allows researchers to choose a set of candidate facial components from the database based on their observation or memory. Fig. 4 illustrates the procedure for creating a computerized facial sketch using FACES 4.0 by choosing facial components (e.g., hairstyle, head shape, eye

TABLE 4
Various Attributes of the Files in the Database

Subset	#Variations	#Participants	#Images
2D	Expressions Accessory Camera position	100	4,100
Thermal	Expressions Accessory Camera position	100	1,400
NIR	Camera position	100	3,600
3D	Point Cloud LYTRO-3D	100	200
Video	RGB	100	—
Computerized Sketch	Frontal	100	100

brows, eyes, nose, mouth, jaw shape, mustaches, beards, goatees, forehead lines, eye lines, smile lines, mouth lines, chin lines, facial markings such as scars, moles, piercings, tattoos and earrings, and using hats, headwear and eyeglasses). To the best of our knowledge, the Tufts Face Database is the first database to contain computerized facial sketches built on portrait sittings instead photographs.

4 How to Use the Database

The Tufts Face Database contains over 10,000 images of 113 participants in total. These images belong to six main subsets: the 2D subset, the thermal subset, the near infrared subset, the 3D subset, video subset and the computerized sketch subset. Raw data and the best quality 100 participants face data can be provided per request. Table 4 summarizes the contents of the best 100 participants from the Tufts database.

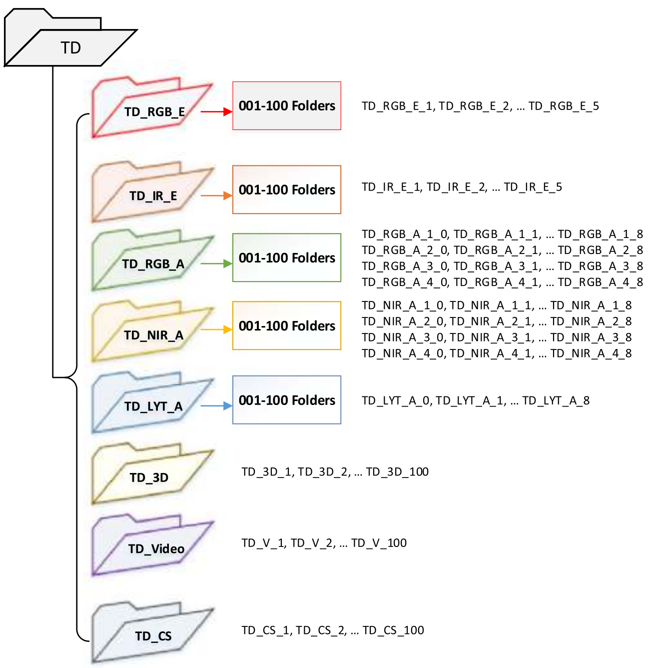


Fig. 5. Database naming convention. Detailed explanation is presented in Section 4.1. We believe our image naming convention will provide a convenient way for indexing.

TABLE 5
Contents in the Tufts Database (Best Quality)

Categories	File format	Average size per file
2D Visible	.jpg	3.45 MB
Thermal	.jpg	187 KB
NIR	.jpg	13.5 MB
3D	.ply	20.8MB
3D LYTRO	.lfr	53 MB
Sketch	.jpg	75.9 KB
Video	.h264	40 MB

4.1 Image Naming Convention

In the Tufts Face Database, the image filename encodes the image information. Its format is described in Fig. 5. It consists of 4 fields and are separated by underline marks as shown below, which provides an easy way for researcher to use.

(1) TD field: TD stands for the Tufts Face Database. It is the common filed that shared by all the files.
(2) Camera and image type fields: RGB stands for 2D visible face image; IR stands for infrared thermal face image; NIR stands for near infrared face images; LYT stands for face.
(3) images that captured by 3D LYTRO camera; 3D stands for point cloud reconstructed 3D face images; Video stands for a short video that can be used to reconstruct the 3D face image and to test face detection and recognition in video data; CS stands for the computerized sketch face images.
(4) Expression field. The initial character "E" represents 5 expression variations: natural expression, smile, open mouth, close eyes and wearing sunglasses.
(5) Camera angle field. The initial character "A" represents 9 different camera positions

4.2 Image Formatting

The raw images of the Tufts Database have different file formats that are shown in the Table 5.

4.3 How to Access

Availability of the database is critical for research transparency in the field. The Tufts Face Database will be publicly available for downloading from our research website on Tufts ECE servers. Researchers who want access the database will need to fill out a request form in order to receive the download permission.

The information on how to obtain a copy of the Tufts Face Database can be found on the project website (http://tdface.ece.tufts.edu/).

5 Conclusion

In this work, we reported our newly developed Tufts Face Database, which we believe will be a valuable resource to facilitate 2D, 3D, thermal, near-infrared, computerized sketch, and heterogeneous facial recognition research for multimedia, forensic, security, biometric, and entertainment applications. The database content and acquisition process are introduced; and the method to obtain the dataset is carefully described. In addition, a comprehensive review on face recognition systems and face datasets are presented.

To date, the Tufts Face Database is the most comprehensive large-scale face dataset. We believe that public availability of this database will enable development and evaluation of face recognition methods across multimodal images.

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