Families In Wild Multimedia: A Multimodal Database for Recognizing Kinship

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Abstract—Kinship, a soft biometric detectable in media, is fundamental for a myriad of use-cases. Despite the difficulty of detecting kinship, annual data challenges using still-images have consistently improved performances and attracted new researchers. Now, systems reach performance levels unforeseeable a decade ago, closing in on performances acceptable to deploy in practice. Like other biometric tasks, we expect systems can receive help from other modalities. We hypothesize that adding modalities to FIW, which has only still-images, will improve performance. Thus, to narrow the gap between research and reality and enhance the power of kinship recognition systems, we extend FIW with multimedia (MM) data (i.e., video, audio, and text captions). Specifically, we introduce the first publicly available multi-task MM kinship dataset. To build FIW MM, we developed machinery to automatically collect, annotate, and prepare the data, requiring minimal human input and no financial cost. The proposed MM corpus allows the problem statements to be more realistic template-based protocols. We show significant improvements in all benchmarks with the added modalities. The results highlight edge cases to inspire future research with different areas of improvement. FIW MM supplies the data needed to increase the potential of automated systems to detect kinship in MM. It also allows experts from diverse fields to collaborate in novel ways.

Index Terms—Kinship Verification, Face Recognition, Talking Faces, Visual Information, Audio, Multimodal, Feature Fusion, Deep Learning, Template Adaptation, Biometrics, Multi-task, Support Vector Machines, Large-scale, Dataset, Convolutional Neural Network.

1 INTRODUCTION

Automated kinship recognition assumes genetic relatedness between individuals is detectable by facial cues. The motivation behind the progress in this arduous task was kinship datasets and advances in face recognition (FR) [1], [2]. The seminal work in visual kinship recognition introduced the first image dataset in 2010 [3]. Later came more prominent and challenging datasets, such as Families In the Wild (FIW) [4] and Tri-Subject Kinship (TSKIN) [5]. After that, researchers proposed methods to match the level of difficulty in these kinship datasets [6], [7].

Conventional FR systems get, store, and recognize human faces automatically. Nowadays, FR, and the vast sub-problems that model visual knowledge from faces, have grown popular in speaker-based problems via audiovisual data (e.g., speaker separation [8], speaker identification [9], [10], cross-modal audio-to-visual or vice-versa [11], emotion recognition in multimedia (MM) [12], [13], and more [14], [15]). The sudden surge of attention to audiovisual data has brought together specialists in biometrics to combine knowledge and find solutions that fuse multi-domain knowledge for best decision-making [16], [17]. The benefits of added biometrics signals reaped in FR intuitively can also enhance existing state-of-the-art (SOTA) in kinship recognition.

FIW [4], [18], the largest and most comprehensive image dataset for kinship recognition, includes 1,000 families with relationships labeled as tree structures: families have family and profile photos (i.e., ≥12 photos), multiple members (i.e., ≥four members), and many faces (i.e., 20 faces on average).

The metadata includes first and last names, genders, bounding box coordinates of faces in photos, and the relationships with all other family members. We chose 200 families of FIW with ≥two members in video data available online. The added biometrics in MM (e.g., the visual dynamics in videos, speech in audio, and spoken words in text captions) should complement the facial images.

The proposed shows that MM improves the SOTA in kinship recognition. Our contributions to the FR, biometric, anthropology, and MM communities are three-fold.

- Built MM database: extended FIW with MM data (i.e., video tracks, speech segments, and text transcripts) via an automatic labeling scheme — >600 audiovisual samples for ≥two members of 200 FIW families). We re-organized FIW MM for the added metadata and paired data at the subject and instance levels, respectively.
- Created protocols and benchmarks: a new paradigm for kinship recognition using MM data. Specifically, the updated experiments to template-based, as there is often a variable number of samples per subject in real-world settings. We are the first to do kinship recognition with multimodal template-based data with family tree labels.
- Proved the advantage of MM: we show an increase in system performance from still-images to still-images and videos, and then, again, with speech signals added — a clear benefit of each added modality is shown. Our analysis highlights the shortcomings of the different media types for future work to address.

This work will attract more scholars to kin-based problems using MM. FIW MM will be accessible online

1. https://web.northeastern.edu/smilelab/fiw/download.html
Figure 1: Sample family of FIW in Multimedia (FIW MM). Top-to-bottom: family-tree labels show faces of members in the immediate family, with subjects of the same generations in the same row; videos, audio, and contextual exemplify sample video pairs of Dr. King Jr. and his daughter Andrea with tracklets of faces in the visual domain and audio data aligned frame-by-frame; randomly selected family photos that contain Dr. Luther King Jr. (note, cropped to fit); faces of Dr. King Jr. from adolescence-to-adulthood. Multiple faces are available for most subjects. Best viewed electronically.
2 Related Works

Attempts to recognize kinship in media began with domesticated animals (e.g., dogs [19] and sheep [20, 21]), as many species recognize their kin through various signals (e.g., touch, smell, visual, and acoustics). From this, we hypothesized that information in MM, besides image-level facial features, can be used to detect kinship in humans better. Hence, knowledge extracted from imagery lacks much information. Modeling more complex signals (e.g., face dynamics and speech in videos) attribute inheritable traits (e.g., expressions, mannerisms, and accents). Nonetheless, getting MM is expensive. We propose a method to collect data and show recognition improvements with MM.

We next review existing work in visual kinship recognition and then research advances audiovisual data for FR.

2.1 Kinship recognition

Computer vision researchers began using faces to recognize kinship about a decade ago, where Feng et al. proposed to model the geometry, color, and low-level visual descriptors extracted from faces to discriminate between Kin and NON-KIN [3]. Others then formulated the problem as various paradigms (e.g., transfer subspace learning [22], 3D face modeling [24], low-level feature descriptions [25], sparse encoding [26], metric learning [27], tri-subject verification [5], adversarial learning [28], ensemble learning [29], video understanding [30–32], and, most recently, video-audio understanding [33]). A common factor is the attempt to improve discriminatory power for classifying face pairs as KIN or NON-KIN; another commonality was the limited sample size and, thus, unrealistic experimental settings.

Robinson et al. introduced a large-scale image dataset to recognize families in still-imagery called FIW [18, 34]. FIW has 1,000 families with an average of 13 family photos, five family members, and 26 faces. It came with benchmarks for 11 pairwise types, with the top performance of the baselines being a fine-tuned CNNs (i.e., SphereFace [1] and Center-loss [35]). This was the beginning of big data in kin-based vision tasks– deep learning could then be used to overcome observed failure cases [36, 37]. Furthermore, new applications such as child appearance prediction [38, 39], and familial privacy protection [40] were made recently.

Nowadays, FIW continues to challenge researchers with various views of image-based tasks. A myriad of methods showed the ability of machinery to use still-images to find kinship in a pair or group of subjects. Nonetheless, only so much information can be extracted from still-images. The dynamics of faces in video data (e.g., mannerisms expressed across frames) have other information, and audio and text transcripts (i.e., contextual data describing the speech and other sounds) can widen the range of cues we model to discriminate between relatives and non-relatives. We propose the first large-scale multimedia dataset for kinship recognition. Specifically, we used the familial data of the FIW image database to build upon the existing resource [18, 34], using the still-images of FIW and adding video, audio, audiovisual, and text data of subjects. Note that the difference between the video and audio compared to the audiovisual is that the former two are single modality and the latter has multiple modalities– audiovisual clips have talking-face tracks aligned with the speech signal. After its predecessor, the database was dubbed FIW MM. En route to bridging research and reality, we follow the protocols of FIW [7], but now can be template-based (i.e., per National Institute of Standards and Technology (NIST) in [41]). Figure 1 depicts a sample family with MM for MLK and his daughter.

An annual data challenge that was based on FIW intended to attract more attention by supplying more structure and incentives for researchers to work on kin-based visual recognition. Namely, the Recognizing Families In the Wild (RFIW) series, which has been held annually since 2017 [42], and with the latest in 2020 [43]. There have been many great attempts on the still-images as a result [44, 45]. Recent surveys [46], tutorials [4], and challenges [7, 47–49] elaborate on RFIW and the various submissions.

2.2 Audiovisual data

The big archetypal data used for audiovisual identification problems are Voxceleb [9] and Voxceleb2 [10]. Like FIW MM, the datasets were acquired by extending image collections (i.e., Voxceleb and Voxceleb2 extended of the VGGFace [50] and VGGFace2 [51], respectively). Currently, the primary usage of Voxceleb is in speaker-based tasks, such as using the audiovisual data to detect and classify the speaker by the who and the when [8]. Other speaker-centric problems have been proposed using the Voxceleb

Table 1: Commonly used acronyms and variables.

| DB Terms       | FID | MID | PID | VID | BB   | SS  | SBS  | FDD | FS   | MD   | MS   |
|----------------|-----|-----|-----|-----|------|-----|------|-----|------|------|------|
| Pair-types     |     |     |     |     | brother-brother | sister-sister | brother-sister | father-daughter | father-son | mother-daughter | mother-son |
| Metrics        |     |     |     |     |     |     |     |     |     |     |     |
| Task / solution| SVM | TA  |     |     |     |     |     |     |     |     |     |
| P              |     |     |     |     |     |     |     |     |     |     |     |
| G              |     |     |     |     |     |     |     |     |     |     |     |
| X              |     |     |     |     |     |     |     |     |     |     |     |
| x              |     |     |     |     |     |     |     |     |     |     |     |
| x+             |     |     |     |     |     |     |     |     |     |     |     |
| x−             |     |     |     |     |     |     |     |     |     |     |     |
| z              |     |     |     |     |     |     |     |     |     |     |     |
| Np             |     |     |     |     |     |     |     |     |     |     |     |
| Nn             |     |     |     |     |     |     |     |     |     |     |     |

| Tri-Pairs      |     |     |     |     |     |     |     |     |     |     |     |
| FMD            |     |     |     |     |     |     |     |     |     |     |     |
| FMS            |     |     |     |     |     |     |     |     |     |     |     |

| Metrics        |     |     |     |     |     |     |     |     |     |     |     |
| CMC            |     |     |     |     |     |     |     |     |     |     |     |
| DET            |     |     |     |     |     |     |     |     |     |     |     |
| TAR            |     |     |     |     |     |     |     |     |     |     |     |
| ROC            |     |     |     |     |     |     |     |     |     |     |     |
| TAR            |     |     |     |     |     |     |     |     |     |     |     |
| TAR            |     |     |     |     |     |     |     |     |     |     |     |
| FR             |     |     |     |     |     |     |     |     |     |     |     |
| TA             |     |     |     |     |     |     |     |     |     |     |     |

| Experimental   |     |     |     |     |     |     |     |     |     |     |     |
| P              |     |     |     |     |     |     |     |     |     |     |     |
| G              |     |     |     |     |     |     |     |     |     |     |     |
| X              |     |     |     |     |     |     |     |     |     |     |     |
| x              |     |     |     |     |     |     |     |     |     |     |     |
| x+             |     |     |     |     |     |     |     |     |     |     |     |
| x−             |     |     |     |     |     |     |     |     |     |     |     |
| z              |     |     |     |     |     |     |     |     |     |     |     |
| Np             |     |     |     |     |     |     |     |     |     |     |     |
| Nn             |     |     |     |     |     |     |     |     |     |     |     |

| Tri-Pairs      |     |     |     |     |     |     |     |     |     |     |     |
| FMD            |     |     |     |     |     |     |     |     |     |     |     |
| FMS            |     |     |     |     |     |     |     |     |     |     |     |

| Metrics        |     |     |     |     |     |     |     |     |     |     |     |
| CMC            |     |     |     |     |     |     |     |     |     |     |     |
| DET            |     |     |     |     |     |     |     |     |     |     |     |
| TAR            |     |     |     |     |     |     |     |     |     |     |     |
| ROC            |     |     |     |     |     |     |     |     |     |     |     |
| TAR            |     |     |     |     |     |     |     |     |     |     |     |
| TAR            |     |     |     |     |     |     |     |     |     |     |     |
| FR             |     |     |     |     |     |     |     |     |     |     |     |
| TA             |     |     |     |     |     |     |     |     |     |     |     |

| Experimental   |     |     |     |     |     |     |     |     |     |     |     |
| P              |     |     |     |     |     |     |     |     |     |     |     |
| G              |     |     |     |     |     |     |     |     |     |     |     |
| X              |     |     |     |     |     |     |     |     |     |     |     |
| x              |     |     |     |     |     |     |     |     |     |     |     |
| x+             |     |     |     |     |     |     |     |     |     |     |     |
| x−             |     |     |     |     |     |     |     |     |     |     |     |
| z              |     |     |     |     |     |     |     |     |     |     |     |
| Np             |     |     |     |     |     |     |     |     |     |     |     |
| Nn             |     |     |     |     |     |     |     |     |     |     |     |
collections, like to enhance speech signals [52], to detect when and where the speaking face is visible [53], and when the audio and mouth motions infer the lips and sound are in sync [54]. Nonetheless, the lip-reading task predates the larger Voxceleb with older lip-reading datasets [55], [56].

It is worth highlighting that these audiovisual databases were instrumental in applied research as well (e.g., generating talking-faces [57], where the input is a still-image face and a stream of audio, and the output frames mocking the audio with the faces as if the input face was regurgitating the audio clip). In [58], face frames were generated from a still-image and audio clip, with pose information added as a control signal for the synthesized output. Furthermore, Voxceleb predicted emotion labels via its signals to automatically infer ground-truth [59].

Minimal attempts to recognize kinship in audiovisual data have been made. Most relevant was in [53], where the authors collected 400 pairs. Wu et al. certainly proved the core hypothesis of this work—multimedia can enhance our ability to automatically detect kinship in humans— as was clearly shown in their work [33]. However, the sample size was limited in the number of pairs and the types of labels, as there is no family tree structure nor multiple samples per member (i.e., age-varying), as is the case in our much more extensive and comprehensive FIW MM.

3 THE FIW-MM DATABASE

FIW MM extended the existing paired faces of FIW via an automated labeling pipeline that allowed the proposed data to be acquired with no financial cost and minimal human input (Figure 2). Specifically, FIW allowed us to find who, when, and where a family member appeared in the video. We chose 200 (of the 1,000) FIW families with 2-5 members in 1-3 YouTube videos. Hence, FIW MM consists
of 550 subjects in 660 videos. We obtained three types of data per subject per video: (1) non-speaking face tracks (i.e., visual only), (2) speech segments (i.e., audio only), and (3) face tracks of the speaker (i.e., audiovisual). Timestamps were set for the start and end frames, along with the bounding box information for the face tracks. In this way, overlap in samples was identifiable.

Let us next cover the data specifications, along with a detailed description of our automatic labeling pipeline.

### 3.1 Specifications

The goal was to extend FIW in the number of samples and the types of media. Plus, improved experimental protocols. Recalling that FIW supplies name metadata and face images for multiple members of 1,000 families, we used this from the 200 families. For quick reference, common acronyms and symbols are in Table 1.

Following the convention of the original FIW, the indices of the topmost level of the database were unique Family IDs (FIDs), which have M Member IDs (MIDs) for M family members. Each FID is represented by a relationship matrix of size M (i.e., a row and a column added per MIDs), along with the gender information for each member. Thus, FIW is organized with 1,000 folders (i.e., one per FID, F0001-F1000), each with a relationship matrix that relates the M MIDs that have face data stored in subfolders (e.g., family F0009 has M = 7, meaning the folder contains 7 MID folders, MID1, ..., MID7). The same scheme is adopted for FIW MM, with the difference being that the MID folders now have a folder per media type (i.e., subdirectory images added to MID folder for which existing face images are now stored). Besides, folders for other media types were added.

### 3.2 Data pipeline

Inspired by earlier work, such as FIW and VoxCeleb (i.e., labeling families) and VoxCeleb (i.e., labeling audiovisual data), we formed the basis for our pipeline. From this, three modality-specific branches processed the data independently. Specifically, the branches process the video, audio, and audiovisual modalities. Furthermore, branch-specific events are recorded by the frame number and used to summarize instances that are propagated between records.

The following subsections are numbered according to the yellow circle callouts in Figure 2.

**Step 1. Raw data resource.** A single-family with at least two members on YouTube was selected (i.e., families with only one member with MM would be useless). Video URLs were queried per unique Video IDs (VIDs) (i.e., v1, ..., vN for N videos). The faces were either interview-style (e.g., with only a news anchor in a plain room answering scripted questions) or face-time clips (i.e., self-recordings with the subject speaking directly to the camera). Also, the ethnicity for subjects was manually collected.

We used Pypi’s youtube-dl to download YouTube videos by URL: each renamed to its VID and stored as an MKV file, along with TXT with captions when available. The raw data consists of the original MKV for the audiovisual branch, audio-only (WAV), and visual-only (MP4) extracted with FFmpeg assuming 25 FPS.

**Step 2. Event records.** Before branching, blank (sequential) tabular records were instantiated for the duration of the video—one record per branch denoted 3-5 (i.e., audio, visual, and audiovisual event records). These are later compared to share knowledge between the branches to help filter out samples of the subject of interest. In essence, the mutual information across records at a given instance (i.e., frame-step) is used to imply matches, contradictions, and non-matches across modalities (i.e., a means to propagate labels across modalities). The usage of set theory helps to both confirm matches and filter out non-matches. Although unique to our problem, the concept of using logic across events to parse videos has been done (e.g., [60]); however, opposed to high-level semantics like types of objects, we care about the more straightforward tasks of a face or no face, speech or not, visible or unseen, and then the same or different subject. Furthermore, doing this increases the random chance by adding more evidence across records.

Specifically, and for one video simultaneously, the three-event records are instantiated with zero event entries. Then, events of each branch are recorded. The type of event is later described for each branch: like branch 3, visual branch, the events are face tracks that is a match with BB coordinates recorded for all frames of the shot; the audio branch consists of instances that each of the k speakers pronounces utterances; the record for the audiovisual branch is when the speaker is visible in the current frame. Then, by propagating the frame number that the subject of interest appears, the other audio instances with the same speaker and the frames where the speaker is visible can be inferred by finding intersecting events between the three records.

**Step 3. Visual branch.** A video was first parsed into scenes by using two global measures and with the assumption that, statistically, neighboring frames of the same shot will match as close as 90% when comparing HSV (i.e., color) and local binary patterns (i.e., texture) features. The features were extracted and used to parameterize two probabilistic representations per frame (i.e., one per feature). Then, neighboring frames were measured via KL-Divergence and compared with a threshold of 0.1 [62]. A pair of frames that scored below the threshold were assumed to be shot boundary frames for V videos of size T_i, i.e., v_i ∈ {1, 2, ..., C} represents all shots detected in the i-th video. The first, last, and the frame closest to the centroid (i.e., in color and texture) were used as the shot: the three frames were run through an MTCNN face detector [65], and for those without at least one face detection were assumed face-less scenes. Otherwise, the clips with face detections had as many as five more frames sampled and passed to the face detector, and then all faces were encoded and compared to the faces for members of the respective family in FIW. Events were then recorded for the face tracks that matched the subject of interest. Note that this could to quickly drop unwanted data and reduce noise in events assumed by the other branches.

Faces were encoded with ArcFace via the architecture, settings, and matcher of [64]. Specifically,

$$d_{\text{boolean}}(x_i, x_j) = d(x_i, x_j) \leq \theta,$$

where the matcher $d_{\text{boolean}}$ compared the $i^{\text{th}}$-to-$j^{\text{th}}$ face encoding of FIW. Hence, $d_{\text{boolean}}$ is the decision boundary
in score space— if threshold \( \theta \) is satisfied, assume match; else, non-match. Note that it is currently assumed that \( i \) and \( j \) are from different sets (i.e., with \( J \) labeled samples from FIW and \( I \) face detections from newly collected). The matcher in Eq \( 1 \) was set as cosine similarity the closeness of the L2 normalized \(^{[66]} \) features by \( d_{\text{boolean}}(x_i, x_j) = 1 - d_{\text{L}_2}(x_i, x_j) = \frac{\|z_i - z_j\|_{\text{L}_2}}{\|z_i\|_{\text{L}_2} \cdot \|z_j\|_{\text{L}_2}} > \theta \), where \( z \) represents media encoding. We set \( \theta = 0.2 \) manually for a high recall. This process - including the usage of ArcFace to encode faces - is the matcher used throughout.

In the end, scenes having the subject of interest had all its frames processed by the MTCNN— the bounding box coordinates, fiducials (i.e., 5 points), and confidence scores were recorded for each step. We then processed the BB coordinates to ensure continuity, dropping those without it: the ROI was set on the prior face location, and the IoU was calculated frame-by-frame, which had to surpass a threshold of 0.3. Finally, up to 25 (i.e., \( J \) faces) were sampled per track and passed to \( d_{\text{boolean}} \) with each of the \( I \) labeled faces (i.e., producing \( J \times I \) score matrix). The mean across \( I \) samples produced a single score per \( J \) faces, at which point the value at the 25-percentile was compared to a higher threshold of \( \theta = 0.25 \). Note, the fusion of scores was done to both consider all the existing labeled faces equally while avoiding much weight on any of the few (of \( J \)) potentially low-quality faces. This step alone yielded many face tracks of type match with high confidence.  

**Step 4. Audio branch.** Audio signals were extracted from the videos and saved as high-quality WAV files. For the entire audio clip, we did speaker diarization— the process of detecting utterances of speech (i.e., the when), to then form \( K \) clusters for \( K \) speakers (i.e., the who). Note that the clusters are arbitrarily assigned IDs per video. In the end, a speech detector determined the when, and clusters determined the number of speakers and, thus, the speech segments from the who. The utterance detector used was SpeechRecognizer\(^3\) and clusters were based on models from \(^{[67]} \).

**Step 5. Audiovisual branch.** The aim was to detect when the speaker is in the field of view. Thus, the purpose was to find the frames for which the face and speech were aligned. An intuitive way would be to relate the faces detected, lip motions, and audio— which is at the core of many speaker ID methods in MM \(^{[68]} \). For this, videos were processed using SyncNet \(^{[69]} \), pre-trained from \(^{[70]} \). The output was the BB at frames for which the audio aligned to that face.

The faces tracks belonging to the subject of interest were found and used to record events. Furthermore, these events, compared with the audio events, allowed the cluster holding all speech utterances of the subject of interest formed at Step 4 to be figured out.  

**Step 6. Outputs and DB structure.** The face tracks, audio segments, and audiovisual tracks of the subject of interest are output and retrievable via the final event record (i.e., the three records merged with only positive instances). Thus, the overlap between audio and audiovisual infer which cluster of audio segments belongs to the respective active speaker, while the processing of the visual and comparison to the original FIW allowed for the subject of interest to match up with the active speaker. Any overlap in the data found in the visual branch or audio branch versus the audiovisual was removed as duplicated instances. The face tracks, speech segments, and clips with aligned audiovisual were added to the folder named after media type in the MID folders, along with the final event record (i.e., the event record is enough to parse raw data). Then, the database is \( N \) FID folders with \( M \) MID folders and a relationship matrix.

### 4 Problem Statements

Following the recent RFIW data challenge \(^{[7]} \), we benchmark two kin-based tasks: kinship verification and search & retrieval of family members. In RFIW and the contemporary works in kinship recognition, protocols are image-based, i.e., unimodal, single-shot experiments. By contrast, FIW MM supports multimodal, with added samples and media types (Table \( 2 \)). Provided the MM, protocols are template-based, like with IJB-A \(^{[41]} \).

Kinship verification has been the primary focus of experiments. More recently, the emergence of the more challenging but more practical task of searching for missing family members was supported \(^{[7]} \). We benchmark FIW MM for both tasks. With the difference being the template-based \(^{[41]} \) approaching settings of operational use-cases.

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3. https://github.com/Uberti/speech_recognition
We next provide details for template-based recognition tasks. Then, we describe the tasks: first kinship verification and then search & retrieval of family members. The paragraph structure stays consistent: task overview, data splits and settings, and task-specific metrics.

### 4.1 Definitions and protocols

Template $X$ holds all media for a subject (i.e., images, videos, audio clips). Hence, $X$ consists of samples $x_i$ with a total of $N$ templates for the $n^{th}$ independent piece of media $x_{ni}$ with a size of the sum of all data samples, $N = N_f + N_v + N_a$. We stored features for all samples. Now, the templates include feature vectors, i.e., $F(x) = z$, where $F$ maps face to the feature space via $F(x) \in \mathbb{R}^m$, and with $d$ being the size of the vector. We set a subject-specific template as probe $P$ (i.e., query) or reference $Q$ (i.e., hypothesis). For $1:N$, known subjects were from a known family, and templates enrolled in gallery $G$. Then, at inference, the goal was to match an unseen probe $P$ with $G$, where $|G|$ refers to the number of templates enrolled in the gallery. As mentioned later, for $1:1$-based evaluation, we assume $|G| = 1$ (i.e., compared the template for $P$ with the template of $G$ to decide whether the pair is KIN or NON-KIN). For $|G| > 1$, the one-to-many $1:N$ search & retrieval task outputs ranked lists of template IDs sorted by the likelihood of being a blood relative (e.g., if $|G| = 10$, then template of $P$ will compare with the ten templates of $G$, to generate a list of indices [1, 10] ordered by score compared with probe $P$).

As mentioned, we treat an audio segment (i.e., a clip of a subject speaking without interruptions or significant pauses) as a single piece of media $x$, which is fused to a single representation by averaging across frames. Note that a video may consist of several disjoint tracks, visual, audio, and audiovisual (i.e., aligned). Thus, there are many independent media samples for both the visual and audio modalities. Again, this is the set of media making up template $X$ per subject, which contains various media samples $x$ such that the $j^{th}$ subject can be represented by $k$ media samples as follows: $X_j = F_t(x_{1j}), F_t(x_{2j}), \ldots, F_t(x_{kj})$, where $t$ corresponds to the media type and, hence, the corresponding encoder. From this, $|X_j|$ is the total number of features for subject $j$. The gallery $G$ consists of a set of subjects by $G = \{(X_{1j}, y_1), (X_{2j}, y_2), \ldots, (X_{nj}, y_n)\}$, where $y$ are identity labels for each of the $N$ subjects, and $l \in \{1, 2, \ldots, L\}$ are ground-truth for $L$ families. Each tuple also contains a tag representing the set of $L$ families (i.e., $(X_j, y_j)$, where $l \in \{1, 2, \ldots, L\}$. Further partitioning of the data is done per the requirements of a task. For instance, for the verification, the $i^{th}$ pair of tuples from the same family $\mathbb{P}_m = \{(X_{ij}, y_i)(X_{lj}, y_j)\}$, where $i \neq j$, inherit labels KIN (i.e., match) and relationship type.

Each task consists of a $(\approx60\%)$ train, $(\approx20\%)$ validation, and $(\approx20\%)$ test set. These sets are disjoint in family and subject IDs—sets were generated by splitting family labels, with partitioning that remained constant for all tasks.

### 4.2 Kinship verification

Kinship verification is the simplest of tasks in this challenging and complex problem space. Hence, this one-to-one paradigm is the main view vision researchers have tackled. The task is to figure out whether a face pair are blood relatives (i.e., true kin or match). This face-based problem inherits all the challenges of conventional FR, such as variations in lighting, pose, and occlusion (e.g., sunglasses or beards). Additionally, several challenges specific to kin-based FR are posed by age variations, face pairs that contradict directional relationships (e.g., grandparent-grandchild, where the face image of the grandfather was from a younger age and that of the grandchild was older), bias across subgroups like in FR [43] but amplified for the kin-based data.

The most fundamental question asked in kinship verification and re-asked in all other kinship discrimination tasks is whether a face pair is related. Therefore, kinship verification is the boolean classification of pairs (i.e., $y \in \{KIN \cup NON-KIN\}$). Typically, knowledge of the relationship type is assumed. Thus, supplied the output of the model for a given pair is KIN, then the specific type is implied. Future efforts could incorporate relationship-type signals to advance capabilities of kinship detection systems; however, and as stated upfront, verification provides the simplest of all the benchmarks and, up until now, is the most popular.

#### 4.2.1 Data splits and settings

Conventionally, a query consists of a single face image $x_1$ paired with a second face image $x_2$ (i.e., a one-shot, boolean classification problem with labels $y \in \{KIN, NON-KIN\}$). Put formally, given a set of face-pairs $(x_1, x_2)$, where the number of sample pairs $s \in \{1, 2, \ldots, S\}$ of relationship-type (e.g., mother-son). A set of pair-lists $\mathbb{P} = \{[(x_1, x_2)_1], [(x_1, x_2)_2], \ldots, [(x_1, x_2)_S]\}$ for the $L$ types, and with the label determined by the indicator function $\mathbb{I}$ for a single pair $\mathbb{P}_s \rightarrow \{0, 1\}$, i.e.,

$$\mathbb{I}(\mathbb{P}_s) = \begin{cases} 0 & \text{NON-KIN} \\ 1 & \text{KIN} \end{cases}.$$  

Note, a $\mathbb{P}_s$ consists of a pair of templates and, thus, the task is to decide whether the media of the templates provide...
Table 5: Identification results for Image, Image + Video, and Image + Video + Audio. Specifically, accuracy as a function of rank and mAP scores. The higher, the better.

| Modality   | Fusion      | @1  | @5  | @20 | @50 | mAP |
|------------|-------------|-----|-----|-----|-----|-----|
| Image      | Mean        | 0.29| 0.43| 0.54| 0.64| 0.78| 0.13|
|            | Median      | 0.28| 0.44| 0.52| 0.64| 0.77| 0.13|
|            | Max         | 0.11| 0.19| 0.28| 0.34| 0.52| 0.06|
|            | TA          | 0.31| 0.43| 0.52| 0.63| 0.74| 0.14|
| + Video    | Mean        | 0.30| 0.44| 0.52| 0.64| 0.77| 0.14|
|            | Median      | 0.28| 0.44| 0.50| 0.63| 0.76| 0.14|
|            | Max         | 0.13| 0.21| 0.26| 0.30| 0.44| 0.06|
|            | TA          | 0.34| 0.46| 0.55| 0.68| 0.75| 0.16|
| + Audio    | Mean        | 0.30| 0.44| 0.52| 0.64| 0.77| 0.14|
|            | Median      | 0.28| 0.44| 0.50| 0.63| 0.76| 0.14|
|            | Max         | 0.13| 0.21| 0.26| 0.30| 0.44| 0.06|
|            | TA          | 0.56| 0.59| 0.63| 0.74| 0.78| 0.24|

The data can be further split by the type of relationship $l \rightarrow L$ sets of pairs organized into $L$ disjoint list, meaning $\mathbb{P}_s$ partitioned into $l$ disjoint sets in $\mathbb{P}_s^l$ (Table 3). Specifically, pair-types are brother-brother (BB), sister-sister (SS), or brother-sister (SIBS) of mixed-sex; father-daughter (FD), father-son (FS), mother-daughter (MD), or mother-son (MS); grandfather-granddaughter (GFD), grandfather-grandson (GFS), grandmother-granddaughter (GMD), or grandmother-grandson (GMS); four great grandparent types as well. Hence, $l \in L \rightarrow \{BB, SS, \ldots, GMD, GMS\}$ with $L = 11$. Statistics for all relationship types are listed in Table 2 with the lists of grandparent-grandchild and great-grandparent omitted from the verification task due to insufficient sample counts (i.e., $L = 7$).

As described, FIW MM is organized as templates with many samples from various modalities (i.e., still-face, face tracks, audio, and transcripts (contextual)). Specifically, true IDs $y$ are paired with a template of all media available for the respective subject. In contrast with conventional kinship recognition, where one image is compared to another, $l$ is the respective subject. In contrast with conventional kinship verification accuracy measured performances in verification, 4.2.2 Metrics

Detection Error Trade-off (DET) curves and the average verification accuracy measured performances in verification, along with the TAR scores at specific values of FAR (Table 4). DET curves show error rates for binary classification systems, plotting the false-negative rate (FNR) as a function of FAR. Type II error FNR contributes to the Type I error False-positive rate (FPR), revealing the imposter accepted:

$$\text{FAR} = \text{FPR} = \frac{FP}{N^-} = \frac{FP}{FP + TN},$$

where the number of negatives is $N^-$. The geometric relationships of the metrics related to the score distributions and the choice in threshold show the trade-offs in error rates (i.e., Type I versus Type II error):

$$\text{FNR} = \frac{FN}{N^+} = \frac{FN}{FN + TP}.$$  

Finally, TAR + FNR = 1; therefore, TAR = 1 − FNR.

In summary, various attempts were made for both genuine and imposter pairs, and the scores were saved. Then, by changing the threshold that converts the score to a decision, we could visualize the trade-offs between the different error types (i.e., a lower threshold means fewer rejections of genuine pairs but more accepting of imposter pairs). Thus, the performance of the system is highly dependent on a choice in the threshold, which is the reason DET curves are used in biometrics to see these trade-offs in binary problems.

4.3 Search & retrieval (missing family member)

Kinship identification is organized as a 1:N search and retrieval task, with each subject having one-to-many media samples. Thus, we imitate template-based evaluation protocols [41]. Furthermore, the goal is to find relatives of search subjects (i.e., probes) in a search pool (i.e., gallery).
4.3.1 Data splits and settings
A gallery \( G = \{ g_i \}, (i = 1, ..., N) \) is queried by a set of probes \( P = \{ p_j \}, (j = 1, ..., M) \) for search and retrieval, where \( g_i \) is the \( i^{th} \) template in \( G \) and \( p_j \) is the template of the \( j^{th} \) query subject. As mentioned, a template consists of samples of various modalities. Given a template of MM, various schemes were applied to integrate the identity information from all media components of \( P \).

4.3.2 Metrics
Scores of \( N \) missing children are calculated as
\[
AP(l) = \frac{1}{P_L} \sum_{tp=1}^{P_L} \frac{P_l}{\sum_{tp=1}^{P_l} \frac{tp}{\text{rank}(tp)}},
\]
where average precision (AP) is a function of family \( l \in L \) (i.e., \( |L| = P_L \)) for a given true-positive rate (TPR). All AP scores are averaged to find the mean AP (i.e., mAP):
\[
mAP = \frac{1}{N} \sum_{l=1}^{N} AP(l).
\]

Also, Cumulative Matching Characteristic (CMC) curves as a function of rank enable for analysis between different attempts \([71]\), along with the accuracy at rank 1, 5, and 10.

Our choice in metrics is typical for judging the ranking capabilities of classification (or identification) systems. Like the DET assesses the 1:1 case of verification, CMC measures the 1:m performance in ranking-based problems.

5 BENCHMARKS
5.1 Methodology
The problems of FIW MM have various views—multi-source and multimodal. The former varies in samples and treats the different media types independently until the matching function outputs scores (i.e., late-fusion). The latter demands a method for the early fusion (e.g., feature-level), enhancing performance by using informative samples while ignoring noisy and less discriminating samples. We next describe the modality-specific features (i.e., encoding different media types) and methods of fusion.

5.1.1 Visual features
We represented each visual media sample as the encoding from Arcface CNN \([64]\) (i.e., ResNet-34). MS1M \([72]\) was the train set, which had \( \approx 5.8M \) faces for 85,000 subjects. Faces were detected with MTCNN \([63]\), returning the five facial landmarks (i.e., two eyes, nose, both corners of the mouth). Then, faces were cropped and aligned using a similarity transformation on the five points with reference set by the eye locations. Once cropped, we resized the faces to \( 96 \times 112 \). The RGB (i.e., pixel values of [0, 255]) were center about 0 (i.e., subtracting 127.5) and then standardized (i.e., divided by 128). We passed images through a CNN to map to features—all features were later L2 normalized \([66]\). During training, the batch size was 200, and an SGD optimizer with a momentum of 0.9, weight decay 5e-4, and learning rate starting at 0.1 and decreasing \( 10 \times \) twice, both times when the error leveled. We followed the settings of the SOTA Arcface—a popular choice for an off-the-shelf choice for FR technology and applications \([7]\).

We processed both images and videos as described, with the mapping from image-space to feature-space denoted by \( \mathcal{F}(x) \in \mathbb{R}^d \), where the dimension \( d = 512 \) for ArcFace. Face tracks from video data are fused to a single encoding by average pooling the same track features. We represent a face track of \( M \) frames as \( \hat{z} = \frac{1}{N} \sum_{i=1}^{N} \mathcal{F}(x) \). This reduces the effect of noisy frames and smooths out the final representation to weigh like all other media samples.

5.1.2 Audio features
We encode all speech segments with a SOTA deep learning model \([67]\). Specifically, we trained SqueezeNet \([73]\), a 34-layer ResNet \([74]\), with an angular prototypical loss and optimized with Adam \([75]\) to transform WAV-encoded audio files to a single encoding (i.e., \( f(x) = z \in \mathbb{R}^{512} \)). Thus, per the angular prototypical loss \([76]\), used alongside softmax, minimizes within-class scatter (i.e., penalty formed as the sum of Euclidean distances from all samples of a subject from the mean centroid of the respective mini-batch). Expressly, a support set \( S \) and a query \( Q \) are set in each minibatch on a subject-by-subject basis, with \( Q \) made up of a single utterance to compare with the centroid of \( S \) that consists of all other samples in the mini-batch for that class. Angular prototypical takes advantage of the perks of using centroid prototypes while enhancing by following generalized end-to-end (GE2E) \([77]\) usage of a cosine-based similarity metric. This is scale-invariant, is more robust to feature variance, and helps convergence during training \([78]\).

5.1.3 Naive fusion
We show results from various naive fusion techniques (e.g., average pooling of features and voting of scores). To no surprise, the score-based fusion outperforms the feature-level fusion schemes. Specifically, the mean of all scores, both within a template and comparing templates, further improved by adding the other media types (Table \([4]\)). The gain from each added modality is clear from just the naive score-fusion. Still, the naive fusion methods at the feature level are an ineffective way of combining knowledge. Provided media - media that vary in modality, quality, and discriminative power - a simple, unweighted average across the items of a template does not exploit all information. To better fuse the template, we adapt a model to the template to better discriminate family members.

5.1.4 Feature fusion
Template adaptation (TA) \([79]\) is a form of transfer learning that fuses labeled face features from a source domain with template-specific Support Vector Machines (SVMs) trained on the target domain. We followed probe adaptation settings for kinship verification; for identification (i.e., search & retrieval), we follow gallery adaptation settings. Regardless of the setting, the goal is to train a similarity function from a probe template \( P \) to either a reference template \( Q \) (i.e., similarity \( s(P, Q) \)) or gallery \( G \) (i.e., similarity \( s(P, G) \)) for probe adaptation and gallery adaptation, respectively. Thus, given \( P \), we train an SVM on top of its encoded media in

4. Followed \[https://github.com/deepinsight/insightface\]
Figure 4: Template of an actual FS pair incorrectly classified using score fusion, but correct for TA (i.e., feature fusion). Only a single face is available for the father (left), while all son instances are at an early age (right).

The similarity score is the result of the templates fused. The benefit of SVMs is in the kernel. Specifically, the linear, max-margin modeling scheme of a vanilla SVM has proven effective at separating a non-linear feature space between two classes; (i.e., $i$ and $j$, where $y_{ij} = \pm 1$ for the same (+) and different (−) classes). Thus, the implicit embedding function (i.e., kernel) $K(x_i, x_j, y_{ij}) = \varphi(x_i)\varphi(x_j)$ projects the encoding pair to a non-linear space such that the SVM learns the best hyperplane $\varphi(x_i)K(x_i, x_j) + b = 0$ separating the two classes. This is done on the training set by (1) maximizing the margin and (2) minimizing the loss–weights $\mathbf{w}$ are learned, while bias terms $b$ are set to 1 (i.e., concatenated on $\mathbf{w}$, as an added dimension). Also, $K(x_i, x_j, y_{ij}) = \exp\left[\frac{|x_i - x_j|^2}{\sigma^2}\right]$ for $y_{ij} \in \{-, +\}$ as the respective class (i.e., Gaussian RBF kernel [80] projects all features to a higher dimension). Then, the predicted class is inferred as $\hat{y} = \mathbf{w}^T \varphi(x_i) + b$. We used dlib’s [81] L2 regularized cosine-loss with class-weighted hinge-loss, i.e.,

$$ s(P, Q) = \frac{1}{2} P(q) + \frac{1}{2} Q(p). \quad (3) $$

Along with the sample per subject trained against for probe adaptation, global adaptation samples all other templates in $G$ as added negatives. Again, $N_+ << N_−$. The class imbalance is handled via class-weighted hinge-loss in Eq. [4] with $\lambda_+ = \lambda \frac{N_+ + N_-}{2N_+}$, $\lambda_- = \lambda \frac{N_+ + N_-}{2N_-}$, which are regularization constants inversely proportionate to class frequency. The constant $\lambda$ trades-off between the regularization and loss, which we set to 10 as in earlier work [79].

### 5.1.5 Implementation

The system was implemented in Python, with CNNs for visual and audio from PyTorch’s deep learning framework for each media encoder and SVM from LibSVM. The negative sample set was formed by randomly selecting a single instance from all other families. Hence, investigating and improving the naive means for which we pool negative samples is a promising direction for future work. With that, $N_+$ and $N_−$ are set case-by-case.

### 5.2 Results

System performance boosted with each added modality (Fig. 3 Table 4 and 5). Considering the benchmarks use conventional speech and FR technology and our hypothesis that video and audio boost discrimination, these notable improvements would likely continue to climb supplied a more sophisticated or specific solution. It would be interesting to fuse earlier on and train machinery jointly for audiovisual data. From this, more complex dynamics of facial appearance, along with the corresponding speech signal, could further our knowledge and supply insights.

There was a trend in the type of corrected samples when comparing the score-based fusion to the feature-based (i.e., TA). As shown in Figure 4 the challenge of recognizing kinship from samples of one or more members at an early age is mitigated. TA learns to better discriminate in these conventional failure cases. Additionally, some templates with multiple instances are often better than others when comparing. Hence, TA does not simply average all instances equally, like for naive score-based fusion–fix cases with few samples are most discriminate (Fig. 5).

### 5.3 Discussion

The template-based protocol adds practical value by mimicking the more likely structure posed in operational settings, per NIST [41]. Besides, several other factors make it a more exciting formulation and, therefore, a higher potential for researchers to show off their creativity. For instance, opposed to using a single sample per subject (i.e., one-shot learning), each now is represented in a set of media (i.e., a template). The question now arises - how to best fuse knowledge and incorporate evidence from different modalities and how to best learn from all available MM data? Another consequence of using templates is that the random chance is increased from (1) the knowledge added to the pool (or fuse) from the added modalities, and (2) the gallery size reduces from tens of thousands by nearly tenfold. The latter is not an implication of lessor difficulty but the byproduct of the bias in data [43]. That is, opposed to having one-to-many samples per subject, there is just one
template. Mitigating specific sources of data imbalance (i.e., whether there are thirty samples or just one), a system’s ability to recognize a particular pairing or group affects the metric evenly. In other words, a system may easily recognize a specific parent-child pair regardless of the number of face samples and, so, the number of face pairs. Hence, the impact on the metric is proportional to the number of unique pairs.

Furthermore, for verification, we measured the impact of the different results using the significant test. Expressly, we set the baseline image-only as the null hypothesis to compare an alternative hypothesis set as the different results (i.e., image-only, image and video, and audiovisual). Specifically, comparing baseline to null results in a p-value of 1.000 (i.e., same results). Then, a limited improvement p-value=0.974 (i.e., the smaller, the better) results compared to the mean of image and videos (i.e., videos add samples, but of the similar modality after averaging frames). Significant improvement in p-value=0.024 compared with the naive fusion of MM (i.e., audio and visual), which goes to 0.000 for TA using MM. Thus, this further confirms our claim that kinship recognition systems significantly better the decisions.

6 Future Work

FIW MM pushes the bar for possibilities in automatic recognition of kinship in MM. An immediate next step for research involves gathering experts of different domains, such as those in sequence-to-sequence modeling, whether video (i.e., visual), audio (i.e., speech), contextual (e.g., conversations and parts-of-speech), or early fusing pairs or groups. Let us next discuss a variety of ways that we foresee the data being beneficial and to form a collaboration amongst different research communities and beyond (i.e., although FIW-MM is for non-commercial uses, the resource has high commercial potential and, thus, proof of principle experiments can motivate business moves).

We expect FIW MM to bring anthropology and genealogy experts together with researchers of MM and ML to help find the hidden patterns connecting families in MM. For instance, we showed that simply applying pre-trained models from the speech recognition domain allows for the audio signal to be incorporated for more discriminative power than visual evidence alone. Indeed, there is room to improve over the simple benchmark. Furthermore, high-level semantics (i.e., attributes) like accents, commonly used phrases, and speaker demeanor could boost the overall performance and supply insights by interpretation. Similarly, studies on familial language components and inherited changes, or even deltas across the same generation (i.e., commonalities and differences in siblings’ speech), can too be quite revealing. A similar potential exists for the videos and audiovisual data in model complexity and use-cases.

The family trees, an abundance of data points, rich metadata for individuals, and relationships among MM data – FIW MM could serve as a basis for group-based (i.e., social) data mining. More data can enhance or target specific nature-based studies, traditional ML-based audio, visual, and audiovisual tasks, or even extend this dataset. Fusing audiovisual data is an ongoing, unanswered problem [16]. Note that FIW-MM in its entirety pose more problems than it solves: from the model training to improvements made when dealing with missing or incomplete modalities, and even the data processing and data imbalance; from the underlying roots of the problem to the high-level semantics, similar to modern biometrics systems with audiovisual data, FIW MM is an appropriate step considering the state in visual kinship recognition technology.

Another direction is fusion. We included early and late fusion by merging the media as features and scores, respectively. Scores were fused by naively averaging– ignoring the signal type and assuming all samples should carry the same weight. Fusion can incorporate more sophisticated techniques: cross-modality, selectively choosing the best quality samples or model-based decision trees. This concept, alone, is vastly in need of solutions– whether data fusion, where the input is clips of aligned audiovisual; early-fusion, as we did via TA to fuse at the feature-level; or late-fusion, which we also included by naively averaging scores. Besides, metadata, like relationship types (e.g., directional relationships), genders, age, and other attributes, could indicate final decisions. Hence, there is an abundance of fusion paradigms– none are trivial, yet most hold promise.

Besides, questions concerning bias– trends as a function of gender and ethnicity; properly securing family data, addressing areas of privacy and protection. Furthermore, studies on differences between a diverse pool versus a search pool of mostly similar faces– whether it be a closer look at the effects of age for different relationship types, quantifying the similarity of specific features across different subgroups, and its effects on appearance (i.e., visual data)
and speech (i.e., audio data). As has been a focus in recent works \cite{32,33}, considerations of bias across subgroups, along with attempts to acquire a balanced set of families with respect to individual demographics.

Research topics to spawn off the proposed are vast; the specifics suggested here are limited by our imagination. We expect scholars and experts of other domains to see paradigms not mentioned here: whether it be an improved variant of adapting templates and feature fusion (e.g., \cite{64}), deciding when to fuse, a new method of integration, along with the integration details, are all open research questions.

7 Conclusion

We extended the Families In the Wild (FIW) image dataset for kinship recognition with multimedia (MM) data—1-3 MM samples for 2-4 members from 200 (of 1,000) families we obtained and then renamed FIW in Multimedia (FIW MM), which is the first dataset to provide multimedia data for families in ML-related fields. In addition, we followed new paradigms (i.e., template-based protocols) in both benchmarks (i.e., kinship verification and search & retrieval of family members)–templates mimic a realistic setting, as followed in FR-related problems, but with this a first for kin-based recognition. Our labeling pipeline uses multimodal evidence and a simple feedback schema to use the labeled data of FIW to propagate ground truth for the added modalities. Results improve with each added media type, with the top performance obtained with an early fusion of features of multiple modalities. FIW MM marks a significant milestone for kin-based problems by welcoming experts of other data domains. In addition, FIW MM supports several recognition tasks due to its rich metadata, template-based structure, and multiple modalities.

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