mmFace: 3D Face Recognition with RGB and Millimetre Wave Radar

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ABSTRACT

TODO

1. INTRODUCTION

Facial recognition is an evolving research domain within the field of computer vision, finding extensive use across areas including human-computer interaction, security surveillance, and forensic analysis. Its primary application revolves around biometric authentication, granting individuals access to their devices or restricted zones. This enables a non-intrusive, hands-free means of verifying identity, eliminating the need to memorise passwords. Additionally, facial biometrics are naturally more attainable than other modalities such as fingerprints, palm prints, or iris scans [1].

Since its inception in the 1960s, facial recognition technology has undergone significant growth. Initially pioneered by Bledsoe [2], early systems distinguished faces by comparing manually annotated landmark features such as the nose, eyes, and mouth. In recent years, the emergence of deep learning has reshaped human face classification, leveraging extensive online repositories of face images for improved performance and efficiency. However, these systems predominantly rely on images captured by RGB cameras, leaving them vulnerable to variations in lighting and facial pose [3]. By incorporating depth data and drawing attention to the geometric details of the face, the impact of such environmental factors can be regulated. Furthermore, the transition to three-dimensional facial recognition not only increases accuracy but also bolsters the security of biometric systems against spoofing attacks [4].

1.1 Motivations

The popularity of 3D face recognition is on the rise, evidenced by its adoption in smartphones with the likes of Apple and their Face ID [5] technology. This growing demand has pushed the commercialisation of depth-sensing technology to smaller form factors, facilitating its efficient real-time operation on mobile devices [6]. Face ID, in particular, has garnered a level of security that enables payment authentication within services such as Apple Pay. However, Apple's use of costly proprietary hardware and restrictive patents make it harder for smaller companies to adopt an equally compact and secure face recognition system.

Depth cameras, used in this context, typically employ an active form of acquisition. This involves projecting non-visible light onto the face, which is then reflected back, allowing sensors to gauge and delineate facial features. Lidar cameras, emitting waves in the near-infrared (NIR) spectrum, are the most prevalent choice given their capacity to acquire a dense 3D map of the subject's face [7]. However, they are limited by their inability to penetrate thin materials such as clothing and hair. In contrast, millimetre wave radar (mmWaves) can penetrate such materials and directly reach the skin's dermal layer [8]. This could enable greater performance in scenarios involving facial hair or adverse environmental conditions such as rain or fog.

Research into the efficacy of radar waves for 3D face recognition remains relatively limited, although recent studies indicate promising outcomes [9, 10, 11, 12, 13]. Radar sensors typically offer greater cost efficiency in terms of both acquisition and computation, as they consume less power compared to sensors NIR-based systems. Nevertheless, it is crucial to acknowledge the trade-off, as mmWaves often result in a sparser representation. This could impact recognition accuracy, where precision in detecting and mapping of facial features is paramount. Thus, we aim to address this limitation by integrating information from colour images, potentially paving the way for more resilient and versatile systems.

1.2 Research Contributions

Our work explores the effectiveness of using RGB cameras in conjunction with mmWave radar sensors for 3D facial recognition. Since there are no appropriate datasets available for this purpose, we have collated this data ourselves. We use the Intel RealSense L515 RGB-D camera [14] for photographing individuals' faces. Meanwhile, the Google Soli 60 GHz radar sensor [15] is employed to gather depth information by transmitting and measuring millimetre waves reflected from the target.

We initially planned to gather face data from approximately 50 participants, however, only 21 participants came forward within the limited time frame. We obtained face data under various conditions including diverse poses, lighting settings, and common occlusion scenarios. This comprehensive approach led to a system that demonstrates resilience to environmental factors, in comparison, to systems relying solely on RGB data.

We developed a novel face recognition model using a deep convolutional neural network. This model was trained on the captured data to learn facial features from both the RGB and depth characteristics, simultaneously. We investigated different techniques in fusing these two modalities, aiming to pinpoint the most effective strategy that provides rich and distinctive representations for clean identity separation. The model's effectiveness is benchmarked against prior radar-based facial recognition systems, as well as, a comparison to using each modality independently.

The key contributions of this paper are summarised below:

- Compilation of a diverse face dataset comprising color images and mmWave signatures from 21 participants. The dataset encompasses five different poses, two lighting conditions, and two occlusion scenarios.

- We present *mmFace*, a novel face recognition model that harnesses both modalities yielding a robust system capable of handling common occluding materials and nullifying spoofing attempts. The model exhibits strong generalisation capabilities to unseen faces and discerns between live and fake faces effectively.

- An empirical analysis of seven feature-level fusion methods is conducted to determine the most optimal approach for blending RGB and mmWave facial features.

- Our models and evaluations are open sourced[1] to facilitate further research in small-scale, 3D face identification using mmWave technology.

2. BACKGROUND

2.1 mmWave Radar Technology

Radio Detection and Ranging, or Radar, has been around for decades and plays an instrumental role in fields including space exploration, aviation, and maritime navigation. Recently, the miniaturisation of radar sensors to operate in the millimetre wave band have expanded its applicability to more small-scale domains [6]. mmWave sensing has particularly excelled in autonomous vehicles facilitating object detection for systems such as collision warnings and adaptive cruise control [16]. This is primarily due to its edge over traditional near-infrared waves employed by lidar cameras, specifically in its resilience to atmospheric conditions such as dust, smoke, fog, and rain [17]. This penetrative power of mmWaves make it a promising candidate for reliable facial recognition in uncertain, real-world scenarios.

Another notable example is Google's integration of their Soli sensor into the Pixel 4 smartphones for motion detection and gesture recognition [18]. However, the sensor's potential application to face recognition remains unexplored, presenting a unique research opportunity. Consequently, this is the sensor we used to capture mmWave face signatures during our data collection phase. A key driving factor for this choice is the Soli's miniature form factor of just 6.5 mm $\times$ 5.0 mm, and its use of Frequency Modulated Continuous Wave (FMCW) technology. This is proven to offer superior range resolution in comparison to other modulation techniques thanks to its high pulse compression [19], a vital aspect for extracting accurate facial features. The Soli chip has a relatively low power consumption due to the fact that it sends 16 chirps every burst at a pulse-repetition frequency of 2 kHz, then stops transmitting until the next burst of chirps [20]. Each burst is transmitted at 25 Hz giving an overall transmission duty cycle of 2% meaning the radar chip is turned off during the majority of its operation saving a lot of power for mobile applications.

[1]`https://github.com/StergiousAji/mmFace-3D-Face-Recognition-using-RGB-and-mmWave-Radar`

2.2 Related Work

The exploration of millimetre waves for facial identification represents a relatively new avenue of research, fuelled by the recent commercialisation of radar sensor technology. One of the earliest studies delving into human identification using mmWaves dates back to 2019, conducted by Zhao et al. [21]. While this paper primarily examines the classification of subjects based on their gait and body shape rather than facial features, it underscores the capacity of mmWaves to capture the subtle idiosyncrasies among individuals. These nuanced differences are crucial for machine learning models to accurately distinguish between unique subjects, thereby yielding high class separations.

Following this, Hof et al. [9] introduced an Autoencoder capable of recognising human faces captured by an 802.11ad/y networking chipset operating at a 60 GHz centre frequency (f_c). This Autoencoder effectively encodes mmWave face signatures with sufficient distinction to discriminate between positive and negative instances based on their Mean Squared Error (MSE) against reference embeddings. The study involved an extensive data collection effort, capturing face scans of 206 participants of varying genders and ages, across five different poses: frontal, as well as head rotations of 15° and 25° to the left and right. This dataset was subsequently made available through an IEEE Data Port [22]. While this collection encompasses a wide range of faces, including some individuals with spectacles and beards and, it lacks representation of other common occlusion scenarios, such as head accessories, which our project aims to explore. Additionally, the study utilised a larger sensor with a total of 1024 transmit-receive antenna pairs, noted to capture redundant information. This contrasts with the compact Soli chip designed for smartphone integration. The study simulated the impact of reducing the antenna count to 10, resulting in a significant decrease in the distinctiveness of facial signatures. Encouragingly, increasing the number of neurons in their Neural Network and adding an extra hidden layer could compensate for this loss.

Lim et al. [10] proposes another deep neural network with a more traditional Multi-Layer Perceptron (MLP) architecture where every layer is fully connected to adjacent ones. The study utilised a small-scale, 61 GHz FMCW radar sensor developed by bitsensing Inc. [23], comparable to the Soli with a single transmit and three receiver antennas. The model attained a mean classification accuracy of 92% across eight subjects, surpassing the performance of both, a Support Vector Machine (SVM), and a tree-based Ensemble Learning approach trained on the same face signatures. It is important to note the relatively small-sized dataset used to train the model, raising concerns about potential overfitting as the data is not representative enough. The paper provides limited details on the data collection methodology used, only mentioning that the distances ranged from 30 cm to 50 cm. It can be assumed then that the study likely focussed on frontal poses without any occlusions for all eight subjects. The research also explored the impact of using a single receiving antenna, which resulted in a reduced accuracy of 73.7%. This finding is in line with Hof et al.'s [9] observation that an increased number of receiving antennas can enhance classification accuracy by the ability to capture more nuanced facial features.

During the same time frame, Kim et al. [11] conducted research utilising an identical sensor from bitsensing Inc., which boasted a range resolution of 2.5 cm. Their study introduces a Convolutional Neural Network (CNN) model consisting of three convolutional layers and three fully connected layers. The radar data underwent extensive preprocessing to convert it into a format more akin to images, suitable for the CNN. With a data split of 70%/15%/15% for training, validation, and testing, the model achieved an average classification accuracy of 98.7% on a limited dataset of only three individuals. Notably, the study also investigated the impact of wearing cotton masks. The results indicated a negligible decrease in average classification accuracy by 0.9%, which bodes well for the goals of our project. Nonetheless, it is important to approach these findings with caution due to the small dataset size. It remains uncertain whether this level of performance would hold consistently across a larger group of subjects with more varied occlusions.

Pho et al. [12] adopts a One-Shot Learning approach to the problem. This is where the model is trained with a single or only a few labelled instances, beneficial when there is a lack of training samples available. The proposed method constitutes a Siamese structure of two identical CNNs with shared parameters, mapping the input radar signals into latent space. During both training and testing phases, a distance metric between the outputs of the networks is used to assess the similarity between face inputs. Specifically trained for binary classification, the model receives pairs of face signatures from either the same or different individuals. The same bitsensing Inc. BTS60 chipset, used by Lim et al. and Kim et al. [10, 11], is employed to capture 500 frames of the faces of eight participants. An average classification of 97.6% was achieved, an improvement over the previous deep MLP model by Lim et al. involving the same number of people. t-Stochastic Neighbour Embedding (t-SNE) [24] is then applied for dimensionality reduction. The resulting visualisations demonstrate that the one-shot Siamese network effectively separates each individual's face into exclusive regions, simplifying the classification task. Although a small dataset is used, only encompassing frontal poses with no occlusion settings, the proposed method is well documented and is likely robust against larger datasets.

Challa et al. [13] employs two different machine learning models on the dataset provided via the IEEE port [22]. Their approach began with CNN-based Autoencoders, followed by a Random Forest Ensemble Learning approach. A total of nine Autoencoders were built, each tailored to different frame rates, focusing on compressing and reconstructing the original data from its latent form. The Autoencoders were trained using randomly selected data samples from a subset of 186 face scans. The flattened and labelled outputs were then used to train and test nine discrete Random Forest models using identical hyperparameters, as recommended by the Sci-kit library. This methodology yields impressive results, achieving an average classification accuracy of 99.98% using all 1400 frames per individual. Even when reducing the number of frames to 70 per person, the model maintained a high accuracy of 97.1%. The paper presents an approach that is unique in comparison to the rest of the papers tackling this subject, showcasing an efficient model that is able to be deployed on mobile chips.

Research in this domain focuses exclusively on utilising data from radar sensors, largely driven by concerns surrounding privacy preservation. However, a significant drawback of this approach lies in the extended duration required to capture an accurate facial scan. The sensor typically needs to operate for several seconds, ranging between 10 and 15 seconds, to obtain a detailed scan. Such a time frame proves impractical in real-world scenarios, as it requires the subject to remain motionless for a prolonged period. Thus far, no study has explored the potential benefits of combining radar signatures with corresponding RGB data to enhance facial recognition capabilities. Given the high performance of existing deep learning models using RGB images alone, such as InsightFace [25], integrating these models with mmWave radar data presents a promising avenue. This could expedite face acquisition time while capitalising on the advantages of mmWaves in terms of their resilience to lighting variations and occlusions.

2.3 InsightFace

In the evolving field of face recognition, deep CNNs have emerged as a dominant approach due to their ability to extract discriminative facial features from images. One significant advancement in this area is the InsightFace toolkit, implementing algorithms designed to address the intricacies of face analysis and recognition. Key works include the preliminary ArcFace model, introduced by Deng et al. [25], alongside the robust Face Alignment model by Gho et al. [26]. ArcFace employs a novel Additive Angular Margin Loss to maximise class separability, further enhancing the discriminative power in mapping face images to feature embeddings. However, this method was found to face challenges with label noise, requiring the "cleaning" of many real-world images sourced from the web. To address this, further progress was made with the Sub-center ArcFace model [27], introducing the concept of sub-classes to boost resilience against intra-class variations and label noise. It achieved state-of-the-art performance on many widely used benchmark datasets such as the Labeled Faces in the Wild (LFW) [28] and the YouTube Faces (YTF) datasets [29]. The integration of pretrained models offered by InsightFace into our system enables us to concentrate efforts on enhancing the performance of our model's depth and contour detection capabilities.

2.4 Multimodal Data Fusion Techniques

Multimodality, as defined by Lahat et al. [30], refers to the use and analysis of multiple types of data, potentially arriving from multiple sensors. The idea is to extract and blend salient information gathered by each sensor. The integration of this diverse data lead to outputs with richer representations than what could be achieved by the individual modalities alone.

One common strategy involves merging multiple data modalities before feeding them into a learning model, known as **Early Fusion** or **Data-level Fusion**. This technique entails combining data by eliminating correlations between sensors or fusing data in a common, lower-dimensional space [31]. Methods like Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA) are frequently utilised for this purpose. However, a significant issue with early fusion is ensuring synchronisation between the RGB and radar frames, which is challenging due to their notably different sampling rates. Moreover, the continuous mmWave signals must be discretised to align with the format of the RGB data. An inherent drawback of early fusion is the potential to squash crucial information present within each individual modality, thereby impacting training effectiveness.

Late Fusion, or **Decision-level Fusion**, operates by independently processing distinct data sources through separate models and then integrating them at the decision-making stage. A common approach involves calculating a weighted average of the separate predictions, allowing for the adjustment of the influence of specific modalities [32]. Late fusion is often simpler and more adaptable, proving effective when dealing with highly dissimilar data sources in terms of sampling rate, dimensionality, or unit of measurement. Furthermore, late fusion often yields superior performance since errors from multiple models are managed independently.

Intermediate Fusion, or **Feature-level Fusion**, is rooted in neural network architectures and revolves around the concept of combining different modalities within the feature space, where there is a higher level of abstraction of the raw data. This can range from a basic concatenation of the individual latent embeddings to employing Autoencoders for non-linear feature fusion, as demonstrated by Charte et al. [33]. This approach offers greater versatility than early and late fusions since it allows for the integration of features at various depths within the neural network. However, it can pose challenges such as the risk of overfitting or difficulty in learning relationships between the different modalities.

Each data fusion technique presents its own set of challenges and considerations, necessitating experimentation to determine the most effective approach to merging RGB and mmWave signatures. A variant of late, feature-level fusion, where the embeddings from the final layers of each model are combined, was chosen as the most feasible. It would be challenging to attempt early fusion due to the substantial differences between the two modalities. Such integration would likely require heavy preprocessing of the radar data, potentially involving its conversion into a depth image.

3. METHODOLOGY

3.1 Data Acquisition

TODO: REWRITE Following a thorough research of the field, the next steps involved designing and conducting the data acquisition process necessary to train our proposed model with. These experiments required careful planning since the data collected here directly determines the effectiveness of the resulting model. As found in the related works, it is vital to compile multiple poses in order for the model to learn a comprehensive 3D scan of the individual's face. Furthermore, it induces pose-invariance into the system, accommodating real-world use cases where individuals may not always present an exact frontal pose to the face recognition system. Most studies concentrate on azimuth variations since a person is less likely to tilt or pitch their head by a significant angle in comparison to left and right rotations of the face. For this reason, we will similarly focus on head rotations around the yaw axis. We plan to record facial poses at $0°$, $30°$ and $45°$ azimuth relative to the sensors.

Since this experiment aims to explore the benefits of mmWave sensors in the context of face recognition, two different lighting conditions are incorporated in our data collection experiments. Namely, regular and dim lighting scenarios. We hypothesise that the mmWave face signatures would be unaffected by environmental lighting due to the sensor using its own active illumination of the target face, unlike the RGB camera. Therefore, if the system is able to demonstrate higher accuracy utilising both modalities as opposed to relying solely on RGB data, it would decisively indicate that mmWaves offer resilience against varying lighting conditions.

Finally, we investigate the penetrative power of mmWaves to directly reach the skin through cloth and hair by injecting common occlusion scenarios into our experiments. It would be beneficial for facial recognition systems to be inherently robust against typical obstructions such as glasses, hats, masks and so on. Currently, users would be required to remove such accessories for systems to accurately identify and grant them access to particular devices or areas. With mmWaves, we hypothesise that this may not be needed since facial features could be captured regardless. This could greatly benefit security surveillance where individuals deliberately obscure their faces in order to hide their identities. In our experiment, we capture scenarios both with and without occlusion. Since cotton masks have already been explored by Kim et al. [11], other common items like hats, sunglasses, and scarves are used to mirror day-to-day scenarios.

To ensure a diverse range of facial data, we recruited 21 participants within the tight time frame of the project. Adhering to ethical standards regarding sensitive personal information, our participant pool consists of adults, predominantly university students. While this results in an over-representation of individuals aged 20–25 years, it should not impact our study as age variance is not something that is being explored. A total of 15 scenarios are captured for each participant at a distance of 20 cm from the sensors. Each time the sensors are run for 10 seconds, totalling 150 RGB frames and 3,750 mmWave frames per person.

A photograph of the equipment setup can be observed in Figure 1 showing the Intel Realsense RGB-D camera and the green Soli sensor placed side-by-side on board. The full experiment setup is photographed in Figure 2 with the five poses indicated by the yellow tape.

Figure 1: *Equipment: Intel Realsense L515 RGB-D Camera (left) and the Google's Soli* 60 GHz *radar sensor (right)*

To illustrate the results of the collection process, data samples of a subject are provided in the left half of Figure 3. This grid shows RGB frames recorded from all 15 scenarios, with the three different conditions along the rows and the five pose variations along the columns. For brevity, the conditions are abbreviated as outlined in Table 1.

The radar bursts obtained during the data collection phase are pre-processed through multiple FFT stages to transform

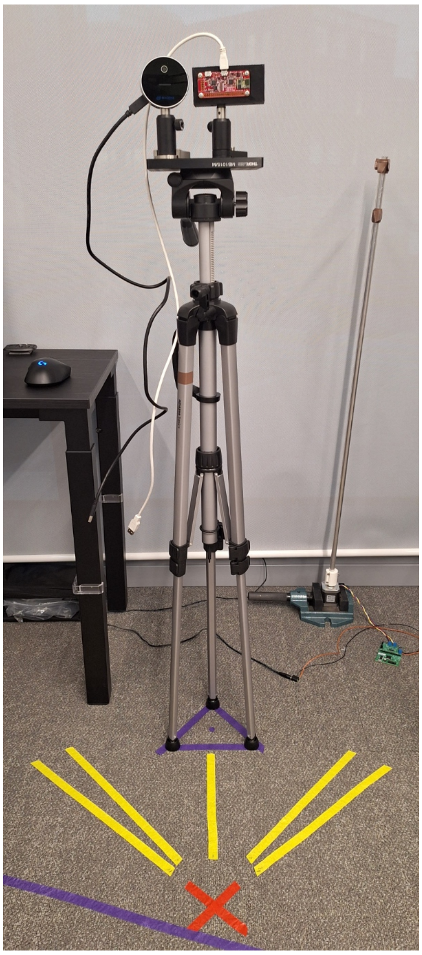

Figure 2: *Experiment setup used for the data acquisition with the equipment mounted on a tripod, the red cross marking the 20 cm distance and the yellow tape indicating the five pose directions*

Abbreviation	Expanded Form
NO	No Occlusion
O	Occlusion
RLC	Regular Lighting Condition
DLC	Dim Lighting Condition

Table 1: *Table displaying full forms for abbreviations describing experiment conditions.*

the raw signals into discretised Complex Range-Doppler (CRD) maps [15, 20]. This is two-dimensional representation of the reflected radar signal, where the range dimension corresponds to the distance of the subject from the Soli sensor and the Doppler dimension corresponds to the radial velocity of the subject towards the sensor. Face scans are collected using the Soli's short configuration which operates at an f_c of 60 GHz, with a maximum bandwidth B of 5.5 GHz, and bursts sampled at 25 Hz. This gives a range resolution of $\frac{c}{2B} = 2.7$ cm, where c denotes the speed of light. The Soli chip has a single transmit and three receiver antennas, each capturing a superposition of scattered reflections from the target. Given that the Intel RealSense captures RGB-D frames at a different sampling rate of 30 frames per second (FPS), timestamp information is also recorded for the possibility of synchronising the two modalities for early data fusion. The right half of Figure 3 illustrates a plot of a single CRD frame of the same subject's face showing the intensities of received signals in discrete 32 Doppler bins along the x-axis and 16 Range bins along the y-axis.

3.2 mmFace

TODO: ARCHITECTURE DESIGN AND CHANGES/IMPROVEMENTS MADE Building on the intuition from Section **??** of the Background chapter, it is clear that the ArcFace model from the InsightFace toolkit emerges as the best choice for our project. It attains state-of-the-art classification results on accepted benchmark sets, outperforming the previous bests such as Facebook's DeepFace [34] and Google's FaceNet [35]. This selection allows us to treat the RGB data processing as a *black-box* framework, enabling us to concentrate efforts on perfecting the radar-based model we are naming, *mmFace*. Furthermore, this facilitates exploration into the various methods in fusing the two modalities as discussed in Section **??**. Figure 5 shows a high-level diagram of the model workflow described here.

Our proposed model, mmFace, will employ a CNN-based architecture, which is particularly effective for processing image-like data.

As explained before, the data fusion techniques we plan to investigate include late, feature-level fusion and late, decision-level fusion. Pure intermediate fusion is not feasible due to the black-box treatment of the InsightFace model making it difficult to integrate information from both modalities within its hidden layers. Nonetheless, late, feature-level fusion remains viable, combining the outputs of the final layers of each model to form an embedding containing both the RGB and radar features. Similarly, decision-level fusion will be explored since this entails mixing the predictions from the individual models. Early fusion presents significant challenges due to the dissimilarities in sampling rates and data formats of the two modalities. The CRD maps must be synchronised and transformed into a depth image-like format before merging with the RGB images. Furthermore, this would require a whole new training cycle with the mmFace model which may be infeasible within the project's time frame. However, should time permit, we will consider investigating this approach.

We plan to adopt a ResNet-based architecture for mmFace due to its refinements over its predecessors like AlexNet [36] and VGGNet [37]. The ResNet framework [38] incorporates "skip connections" and residual blocks to resolve the vanishing gradient problem encountered in VGGNet, allowing scaling of the network beyond the 19-layer limitation. This support for deeper networks provides a strong foundation for the mmFace model for learning the complex radar face signatures.

The dataset, comprising 50 participants, will be divided by subjects into an 80%/10%/10% split for training, validation, and testing. Given the dataset's small size, a larger proportion is allocated for training to ensure the model can learn effectively. Following training, the testing phase will evaluate the distinctiveness of the output face embeddings. For accurate classifications, each person's face must be spatially separable in the high-dimensional embedding space allowing for unambiguous identification. t-SNE visualisations

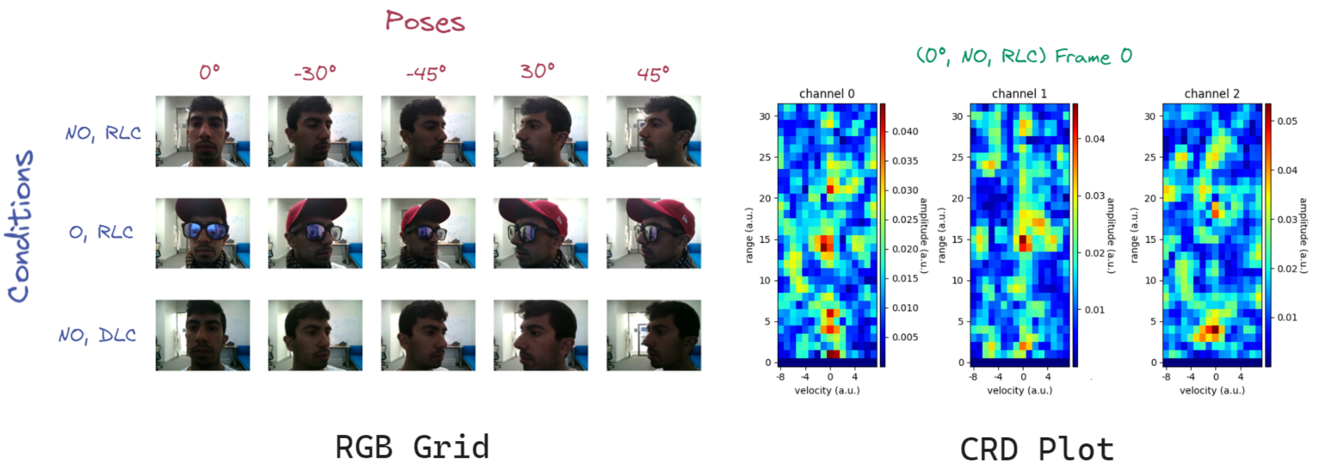

Figure 3: *Data samples collected for Subject 0. The left figure shows the RGB frames of all 15 scenarios organised by pose and condition. The right figure plots a single CRD frame showing amplitudes of reflected waves detected by the three receiving channels of the Soli, categorised into discrete Range-Doppler bins*

[24] will be employed to visually inspect and confirm this is the case by comparing against the original data. In addition, standard classification accuracies will be calculated to verify the model's identity recognition capabilities against randomly selected ground truths. This also allows benchmarking our results against previous studies on radar-based 3D facial recognition.

3.3 Feature-Level Fusion

4. EVALUATION

4.1 Results

5. CONCLUSIONS

5.1 Future Work

Acknowledgments. This is optional; it is a location for you to thank people, most probably your family and your supervisor.

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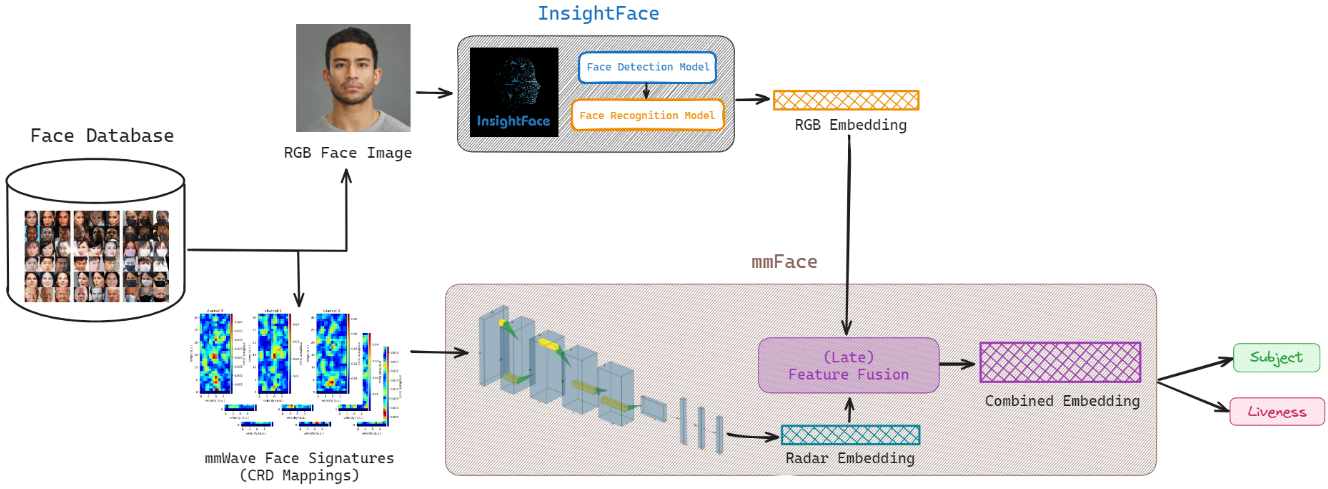

Figure 4: *Workflow Diagram*

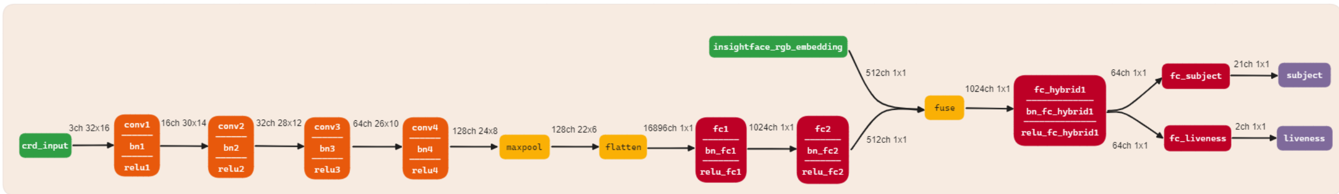

Figure 5: *Architecture Diagram*

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