3D FACE RECOGNITION: A COMPREHENSIVE SURVEY AND ANALYSIS

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MOTIVATION

- TRADITIONAL 2D FACE RECOGNITION SYSTEMS ARE LIMITED BY CHANGES IN LIGHTING, FACIAL EXPRESSIONS, AND POSE VARIATIONS.
- 3D FACE RECOGNITION OFFERS IMPROVED ROBUSTNESS BY CAPTURING GEOMETRIC AND STRUCTURAL INFORMATION OF THE FACE.
- GROWING DEMANDS FOR SECURE AUTHENTICATION IN MOBILE DEVICES, SURVEILLANCE, AND AR/VR DRIVE INNOVATION IN LIGHTWEIGHT AND REAL-TIME SOLUTIONS.

REFERENCES: [1], [2], [3], [4]

INTRODUCTION

- 3D FACE RECOGNITION ANALYZES DEPTH AND SHAPE TO IDENTIFY INDIVIDUALS, OFFERING HIGHER ACCURACY IN UNCONSTRAINED ENVIRONMENTS.
- TYPICAL 3D DATA FORMATS INCLUDE POINT CLOUDS, MESHES, AND DEPTH MAPS.
- THE INTEGRATION OF 3D SENSORS IN CONSUMER DEVICES (E.G., SMARTPHONES, AR HEADSETS) HAS ACCELERATED THE FEASIBILITY OF REAL-WORLD APPLICATIONS.

REFERENCE: [1]

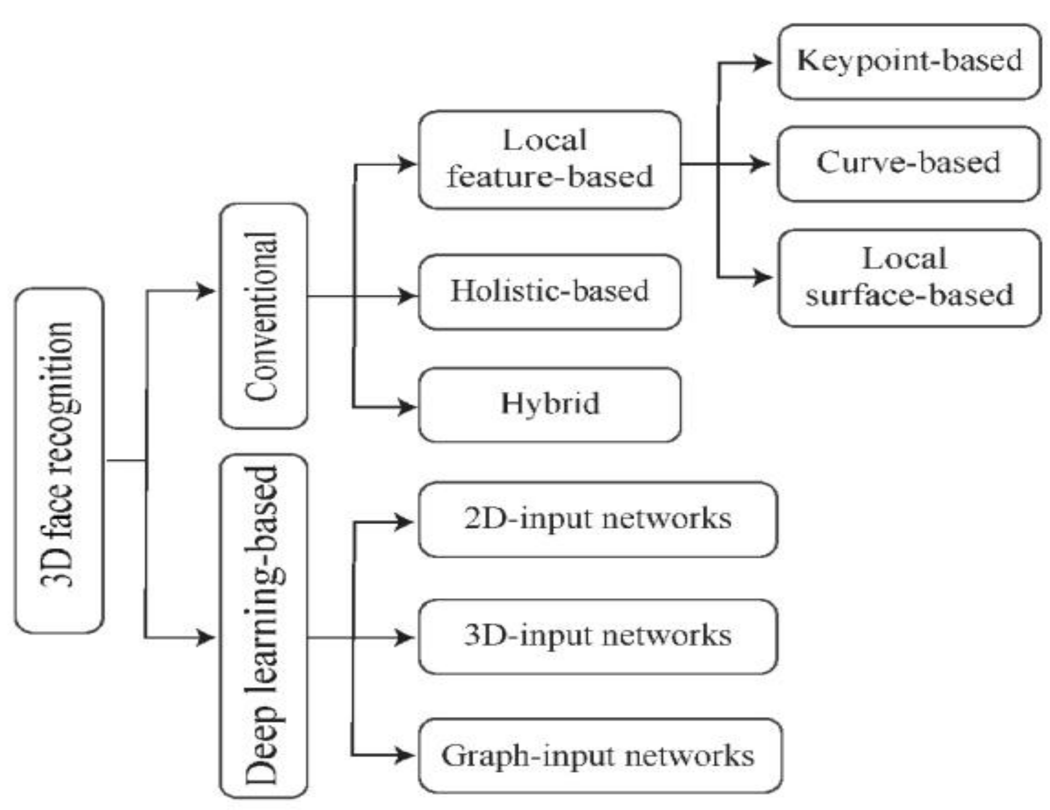

FIG 1: TAXONOMY OF 3D FACE RECOGNITION METHODS.

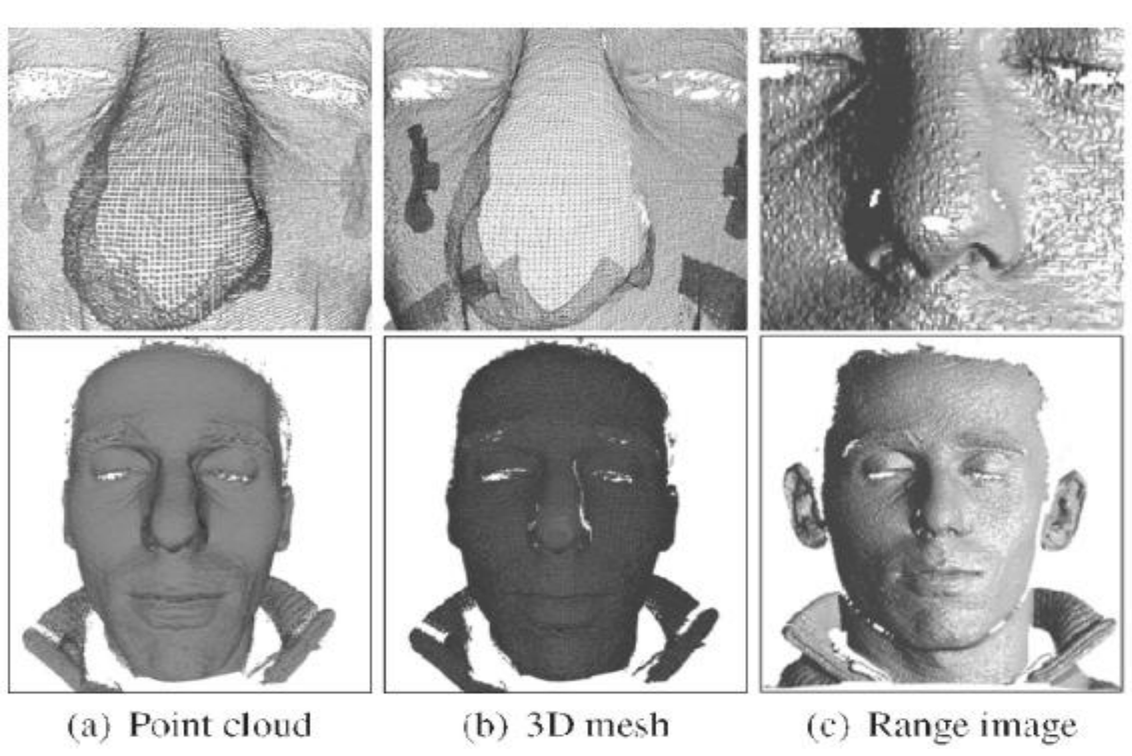

FIG. 2 3D FACE DATA REPRESENTATIONS.

PROBLEM FORMULATION

• **CHALLENGES:**
- DATA QUALITY VARIATION (E.G., LOW-RESOLUTION, SPARSE SCANS)
- OCCLUSIONS AND EXPRESSION-INDUCED DEFORMATIONS
- LACK OF LARGE-SCALE ANNOTATED 3D DATASETS
- HIGH COMPUTATIONAL COSTS

• **GOALS:**
- DESIGN ACCURATE, COMPACT, AND FAST MODELS
- ENHANCE ROBUSTNESS UNDER REAL-WORLD CONDITIONS

REFERENCES: [1], [3], [4]

SIMULATION RESULTS AND DISCUSSION

❑ **CONVENTIONAL APPROACHES**
- **LOCAL METHODS:** FEATURE EXTRACTION FROM FACIAL PARTS (E.G., LBP, SIFT, LDP)
  - ✓ ADVANTAGEOUS IN OCCLUDED SCENARIOS
  - ✓ E.G., LDP SCORED 99.3% ON FRGC V2
- **GLOBAL METHODS:** ENTIRE FACE USED FOR RECOGNITION; COMPUTATIONALLY EFFICIENT
- **HYBRID METHODS:** COMBINE LOCAL + GLOBAL FEATURES; BETTER ACCURACY

REFERENCE: [1]

❑ **DEEP LEARNING-BASED APPROACHES**
- **2D INPUT NETWORKS:** CONVERT 3D DATA TO 2D PROJECTIONS; LEVERAGE CNNS LIKE VGG AND RESNET
  - ✓ E.G., VGG-FACE ACHIEVED 99.2% ON BOSPHORUS
- **3D INPUT NETWORKS:** PROCESS RAW 3D DATA (E.G., POINT CLOUDS)
  - ✓ E.G., POINTNET++ SCORED 99.68% ON BOSPHORUS
- **GRAPH-BASED METHODS:** USE GRAPH CONVOLUTION ON FACIAL GEOMETRY
  - ✓ E.G., FACE-GCN ACHIEVED 88.45% ON BU4DFE
- *REFERENCES:* [1], [5]

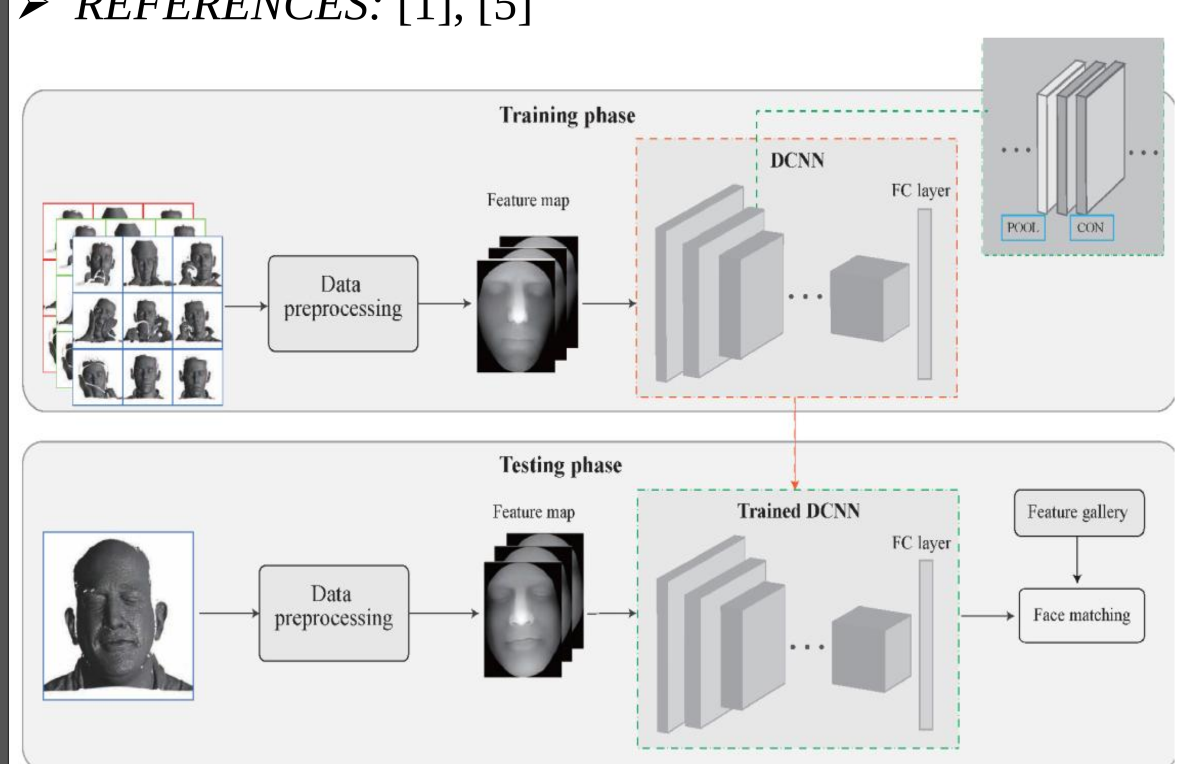

FIG.3: 3D DEEP LEARNING-BASED FACE RECOGNITION

RECENT WORKS

❑ **GEOMETRIC DEEP LEARNING WITH MOBILENETV2**
- LIGHTWEIGHT ARCHITECTURE FOR EDGE DEVICES
- SUITABLE FOR REAL-TIME APPLICATIONS [2]

❑ **MQFNET: MULTI-QUALITY FUSION NETWORK**
- FUSES HIGH- AND LOW-QUALITY INPUTS TO IMPROVE ACCURACY UNDER DEGRADED CONDITIONS [3]

❑ **LOW-QUALITY POINT CLOUD RECOGNITION**
- OPTIMIZED FOR SPARSE, NOISY DATA
- REDUCES MEMORY AND COMPUTATION NEEDS [4]

❑ **POINTNET++ WITH GPMM-BASED AUGMENTATION**
- USES STATISTICAL SHAPE MODELS FOR BETTER GENERALIZATION [5]

DATASETS & DATA FORMATS

- **POPULAR DATASETS:** FRGC V2, BOSPHORUS, BU3D-FE, TEXAS-3D, LOCK3DFACE
- **DATA TYPES:** POINT CLOUDS, DEPTH MAPS / RANGE IMAGES.
- **3D CAPTURE:** ACHIEVED VIA STRUCTURED LIGHT, STEREO VISION, OR TIME-OF-FLIGHT SENSORS (E.G., INTEL REALSENSE, IPHONE TRUEDEPTH).
- **CONVERSION FROM 2D:** MULTIPLE 2D VIEWS OR SHAPE-FROM-SHADING TECHNIQUES CAN ESTIMATE 3D SHAPE FROM 2D PHOTOS, BUT WITH LESS ACCURACY.

REFERENCE: [1]

OBSERVATIONS AND INSIGHTS

- DEEP LEARNING DOMINATES WITH HIGH ACCURACY AND GENERALIZATION
- HYBRID AND GRAPH-BASED METHODS ARE EMERGING AS PROMISING ALTERNATIVES
- AUGMENTATION (E.G., GPMM, GANS) IMPROVES ROBUSTNESS TO DATA VARIABILITY
- *REFERENCES:* [1], [5]

OBSERVATIONS AND INSIGHTS

- EXPLORE LIGHTWEIGHT 3D MODELS OPTIMIZED FOR EDGE DEVICES AND MOBILE PLATFORMS.
- INVESTIGATE DATA-EFFICIENT LEARNING STRATEGIES SUCH AS SELF-SUPERVISED AND FEW-SHOT LEARNING FOR 3D FACE RECOGNITION.
- DEVELOP ROBUST 3D DATA AUGMENTATION TECHNIQUES USING GENERATIVE MODELS (E.G., GANS, 3DMMS)..
- STUDY FUSION OF 3D WITH OTHER MODALITIES (E.G., INFRARED, AUDIO) FOR MULTI-MODAL FACE RECOGNITION.
- DESIGN CUSTOM DATASETS REPRESENTING REGIONAL AND DEMOGRAPHIC DIVERSITY TO ENHANCE FAIRNESS AND GENERALIZATION.

REFERENCES: [1]–[5]

CONCLUSION

- 3D FACE RECOGNITION IS ADVANCING RAPIDLY WITH THE HELP OF DEEP LEARNING, ESPECIALLY UNDER REAL-WORLD, LOW-QUALITY, OR MOBILE CONDITIONS.
- FUTURE DIRECTIONS INCLUDE DATASET ENRICHMENT, REAL-TIME MOBILE DEPLOYMENT, AND LIGHTWEIGHT DEEP ARCHITECTURES.
- THIS POSTER FORMS THE FOUNDATION FOR UPCOMING RESEARCH WORK AIMED AT ADDRESSING THE ABOVE OPEN CHALLENGES.

REFERENCES: [1]–[5]

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