Reference Resolution as a Constraint on Identity Evidence

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Abstract

Resolution changes the information available in a reference and the behavior of the tools used to assess it. This article proposes a resolution study that separates input evidence, generation response, and evaluator sensitivity. ARGUS motivates structured identity references, but no images are resized and no outputs are scored. The design records the complete processing path and uses independent assessment to interpret score changes. It treats resolution as a documented information constraint rather than assuming that a smaller image is a pure intervention on identity.

1. A pixel count does not fully describe the reference

Two files with the same dimensions can contain different amounts of useful detail because of focus, compression, cropping, and earlier resampling. Enlarging a low-resolution image does not restore its original observations. A benchmark that reports only final width and height may therefore hide an important difference in reference evidence. The acquisition and processing history matters when a generation result is attributed to the amount of identity information supplied.

ARGUS uses organized reference views to condition subject-preserving video (Meng et al., 2026b). That setting motivates a controlled question about input resolution while leaving the full generation mechanism outside the present study. This article proposes a design rather than performing a resizing experiment. It does not report an optimal resolution or claim that any particular conditioning module depends on fine detail. Its purpose is to identify what would have to remain fixed for a resolution comparison to be interpretable.

A benchmark's observation count should be accompanied by a description of what an observation is. The LFW pair protocol separates identities from their images and from the comparisons used for verification (Huang et al., 2008). Its documented software access routes also distinguish the ten-fold assessment from development subsets (Pedregosa et al., 2011). Dataset documentation connects those files to their collection and intended purpose (Gebru et al., 2021). A generation benchmark needs an equally explicit account of how a referenced subject becomes a set of output clips and scored frames. Without it, repeated observations may receive unintended weight or cross a supposed assessment boundary. A metadata analysis can establish whether those links are consistent. It should still avoid claiming that consistency of filenames proves recognizability, fair representation, or robustness under viewpoint change. Those are further outcomes requiring appropriate measurements.

An identity score is produced by a measurement system with its own training and assumptions. FaceNet (Schroff et al., 2015), ArcFace (Deng et al., 2018), and CosFace (Wang et al., 2018) offer influential approaches to discriminative face representation. Their outputs should be interpreted in relation to the images and decisions on which they are assessed. VGGFace2 broadens variation within subject observations (Cao et al., 2017), MegaFace makes large distractor populations important (Kemelmacher-Shlizerman et al., 2015), and FairFace addresses imbalance across annotated demographic categories (Kärkkäinen and Joo, 2019). These are complementary evaluation concerns. A generated-video study should not compress them into an unexplained claim that a face benchmark is difficult. It should specify whether difficulty comes from viewpoint, acquisition, distractors, subject population, or the representation itself. Demographic conclusions require appropriate annotations and cannot be inferred merely from identity frequencies or from a generic face-similarity score. A metric's usefulness for one purpose remains an empirical question for another.

2. Distinguishing input processing from measurement processing

A proposed experiment would start from declared source observations and retain their original versions. Each resolution condition would use a documented resizing procedure, including crop, interpolation, compression, and any model preprocessing. The generator's actual received input matters more than the stored file dimensions. If a pipeline internally standardizes images, the study should record that transformation rather than describe externally different files as though they necessarily create different effective inputs.

The evaluator's reference path should be controlled separately. One comparison could hold generated clips fixed while changing the reference used for scoring. Another could hold the scoring reference fixed while changing the generator's input. These contrasts distinguish measurement sensitivity from changes in generated content. A complete workflow comparison can change both, but its result should remain a workflow effect rather than being attributed automatically to one stage without evidence.

Independent judgments could examine whether the subject remains recognizable and whether the requested scene is executed. Reviewers would receive a declared reference presentation, with uncertainty retained where evidence is inadequate. The analysis should record detector failures or unavailable automated scores. Removing difficult low-resolution cases after processing can make a metric appear stable by narrowing its coverage. Coverage and conditional measurement performance therefore belong together in the resulting report.

A large collection of measurements does not guarantee a large collection of independent cases. Repeated observations can share unrecorded acquisition conditions or a common source, making row-level uncertainty misleading. White's covariance estimator addresses heteroskedasticity within a specified regression (White, 1980), while cluster methods address a declared form of grouped dependence (Cameron and Miller, 2015). Neither approach repairs a poorly defined outcome or establishes representativeness of the observed sample. A report should identify the number of groups, their relative sizes, and the reason for selecting the grouping level. When only a few independent groups are available, apparently precise numerical intervals warrant particular caution. This is a limitation of the evidence structure, rather than a reason to count correlated measurements as fresh observations.

Describing a contrast accurately can be more valuable than giving it an unjustified mechanistic name. A causal interpretation needs assumptions about how exposure and outcome arose, including selection into the analyzed sample. Causal diagrams provide a language for those assumptions (Greenland et al., 1999). If several alternative metrics or partitions are examined, the investigator should also account for the freedom to select whichever result appears strongest. False-discovery control is relevant to explicit collections of statistical tests (Benjamini and Hochberg, 1995), while a descriptive sensitivity analysis should be presented as such. A model can fit the observed rows well and still leave the principal explanation unresolved. Reporting that boundary preserves the value of the observation without overstating what adjustment or a significance threshold has established.

Subject conditioning is not identical to measuring the resulting subject. DreamBooth studies subject-driven generation through model adaptation (Ruiz et al., 2022), whereas IP-Adapter develops image prompting compatible with text conditioning (Ye et al., 2023). The reference evidence available to those mechanisms should be matched or explicitly described in a comparison. Generic representations also have different training purposes: CLIP connects imagery to language (Radford et al., 2021), while DINO investigates self-supervised visual features (Caron et al., 2021). Either can contribute to a measurement pipeline, but neither automatically defines human identity across generated motion. A study should separate input fidelity, recognizability, and obedience to scene instructions. It should also retain

cases in which these objectives conflict. An image-conditioning mechanism can reproduce an accessory or background very well while leaving a more important identity requirement unresolved. Measuring those conflicts directly is more informative than declaring every increase in reference similarity a successful preservation of the person.

3. What a resolution response would mean

A difference between resolution conditions may reveal an operational constraint, but it does not identify a unique visual mechanism. Resizing can alter boundaries, local contrast, and artifacts alongside fine detail. A further mechanism study would need appropriate interventions and observations. The proposed resolution comparison is still useful without that stronger explanation: it can show how a documented workflow behaves when its input evidence is reduced by a specified process.

Repeated generations should be linked to their subject, source reference, instruction, and sample settings. A favorable selected clip at one resolution should not be compared with an unselected clip at another. Matched generation budgets and common assessment rules help separate input processing from search opportunity. The report should preserve failed attempts and state whether uncertainty calculations generalize over subjects, instructions, random samples, or only the observed collection.

The final result should identify the range of source qualities and views represented. A response measured using high-quality frontal portraits cannot establish the same relationship for compressed profile images or references with substantial occlusion. An observational collection can document those differences, while a controlled extension can isolate selected processing changes. Keeping those evidence types distinct allows a useful practical finding without turning one resizing curve into a universal claim about the minimum information needed to preserve identity.

The protected assessment population should be defined before investigators inspect detailed failures. Once a collection of cases guides repeated revisions, it has become development information even if its filenames still carry an evaluation label. Cross-validation for dependent data treats the grouping of observations as a substantive design decision (Roberts et al., 2017). Research on model selection likewise shows why tuning and final error estimation should not reuse the same information (Varma and Simon, 2006). A practical record therefore distinguishes fitting data, diagnostic examples, validation data, and the final external assessment. Where only a fixed public table is available, a descriptive analysis remains legitimate, but it should not be renamed a held-out prediction experiment without generating and assessing predictions under a protected split.

An automated measurement should not inherit the authority of its training labels without a direct assessment of use. The relevant checks include systematic disagreement with the intended procedure (Bland and Altman, 1986) and calibration of any probability claims (Guo et al., 2017). Ranking performance, absolute accuracy, and confidence reliability are distinct outcomes. A study can improve one while leaving the others unchanged. Keeping the measurements separate permits examination of those tradeoffs and avoids implying that one favorable statistic establishes all aspects of validity. When independent judgments are unavailable, the limitation should remain part of the result. The absence of a target observation cannot be repaired by combining several correlated proxies into a more elaborate total score.

4. Connecting an identity claim to its observations

An identity evaluation becomes more informative when it retains the other properties of a generated clip. VBench's multiple dimensions (Huang et al., 2023) help motivate this decomposition. Structural similarity (Wang et al., 2004) compares a particular aspect of image structure; learned perceptual similarity (Zhang et al., 2018) uses another representation; video-distribution metrics (Unterthiner et al., 2018) incorporate temporal visual features. None alone establishes a stable person through every pose and event. A study should identify the relevant time windows and examine local failures as well as sequence averages. It should also distinguish an identity evaluator's inability to score a frame from the generator's inability to preserve a subject. Those are different observations with different remedies. A measurement profile linked to the original clip permits this distinction to be checked and avoids attributing broad capability to a favorable average obtained only on easily measurable views.

Difficult cases can disappear at several stages: data eligibility, generation, measurement, and final scoring. Each exclusion changes the population represented by the reported result. Coverage-aware evaluation makes those decisions visible (Geifman and El-Yaniv, 2017). A confidence score should also be checked when the input distribution changes, because uncertainty under shift is an empirical property rather than a guarantee of the model interface (Ovadia et al., 2019). An informative record preserves failures to produce an output and failures to obtain a valid measurement. Treating either as absent data without explanation can inflate apparent reliability. A proposed method should state its unsupported conditions and test the boundary between accepted and rejected cases as carefully as the quality of its successful outputs.

Reproducibility begins with preserving which scientific objects are being linked. Stable identifiers and reusable metadata help connect inputs, reference observations, model versions, and reported outcomes (Wilkinson et al., 2016). The scoring pipeline also has dependencies that can change the interpretation of a result: preprocessing, representation checkpoints, thresholds, and aggregation code can all matter (Sculley et al., 2015). A compact release should retain those decisions rather than only the final mean. Where source data cannot be redistributed, an access description and hashes can still identify the analyzed inputs. This record allows later users to distinguish a change in the underlying system from a change in how the system was measured. Reproducibility is therefore part of interpretation, not simply a final packaging step.

5. Conclusion

Resolution studies need source histories and separate controls for generation input and scoring input. The proposed design retains processing details, coverage, independent judgments, and sampling effort. It reports no new resolution response. Its contribution is to make future input-quality evidence interpretable: a change in score can be connected to a declared workflow intervention while uncertainty remains about unmeasured visual mechanisms and reference conditions outside the tested collection.

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