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(54) **SYSTEM AND METHOD FOR MATCHING A VOICE SAMPLE TO A FACIAL IMAGE BASED ON VOICE AND IMAGE METAPROPERTIES**

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G06V 10/774	(2022.01)
G06V 10/776	(2022.01)
G06V 40/16	(2022.01)
G10L 17/02	(2013.01)
G10L 17/04	(2013.01)
G10L 17/10	(2013.01)

(52) **U.S. Cl.**
CPC ***G06V 40/70*** (2022.01); ***G06V 10/764*** (2022.01); ***G06V 10/774*** (2022.01); ***G06V 10/776*** (2022.01); ***G06V 40/172*** (2022.01); ***G06V 40/179*** (2022.01); ***G10L 17/02*** (2013.01); ***G10L 17/04*** (2013.01); ***G10L 17/10*** (2013.01); *G06V 2201/10* (2022.01)

(58) **Field of Classification Search**
None
See application file for complete search history.

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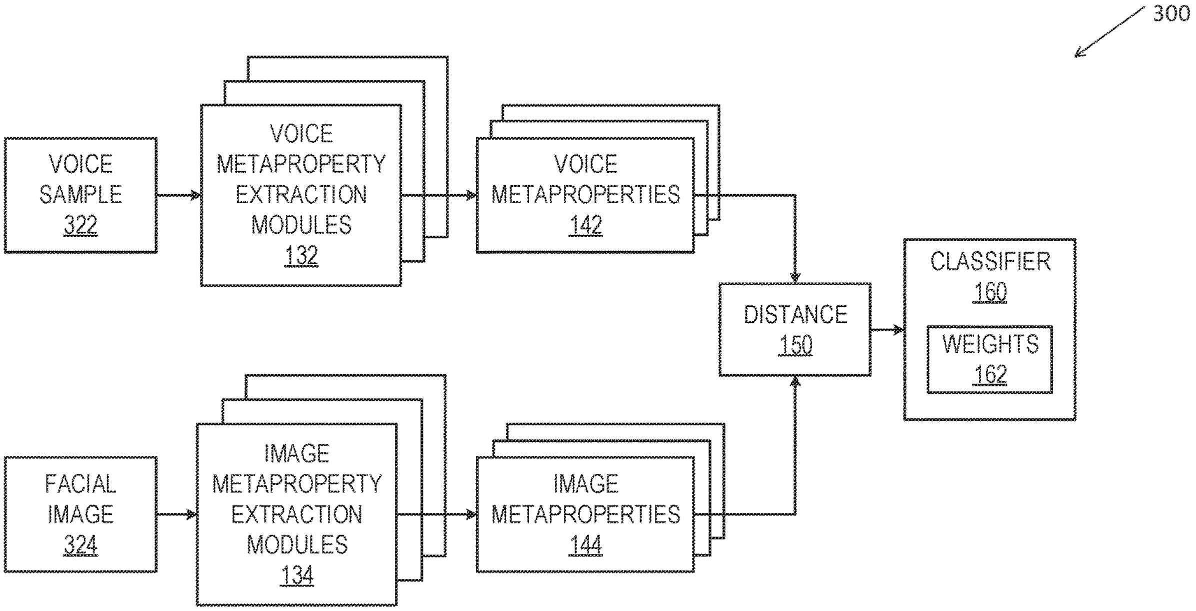
(57) **ABSTRACT**

System and method for matching a voice sample to a facial image may include, using a processor: obtaining a voice sample and a facial image; calculating a plurality of voice metaproperties from the voice sample; calculating a plurality of image metaproperties from image sample, where each of the image metaproperties corresponds to one of the voice metaproperties; and determining a level of match between the voice sample and the facial image, based on the plurality of voice metaproperties and the plurality of image metaproperties.

12 Claims, 5 Drawing Sheets



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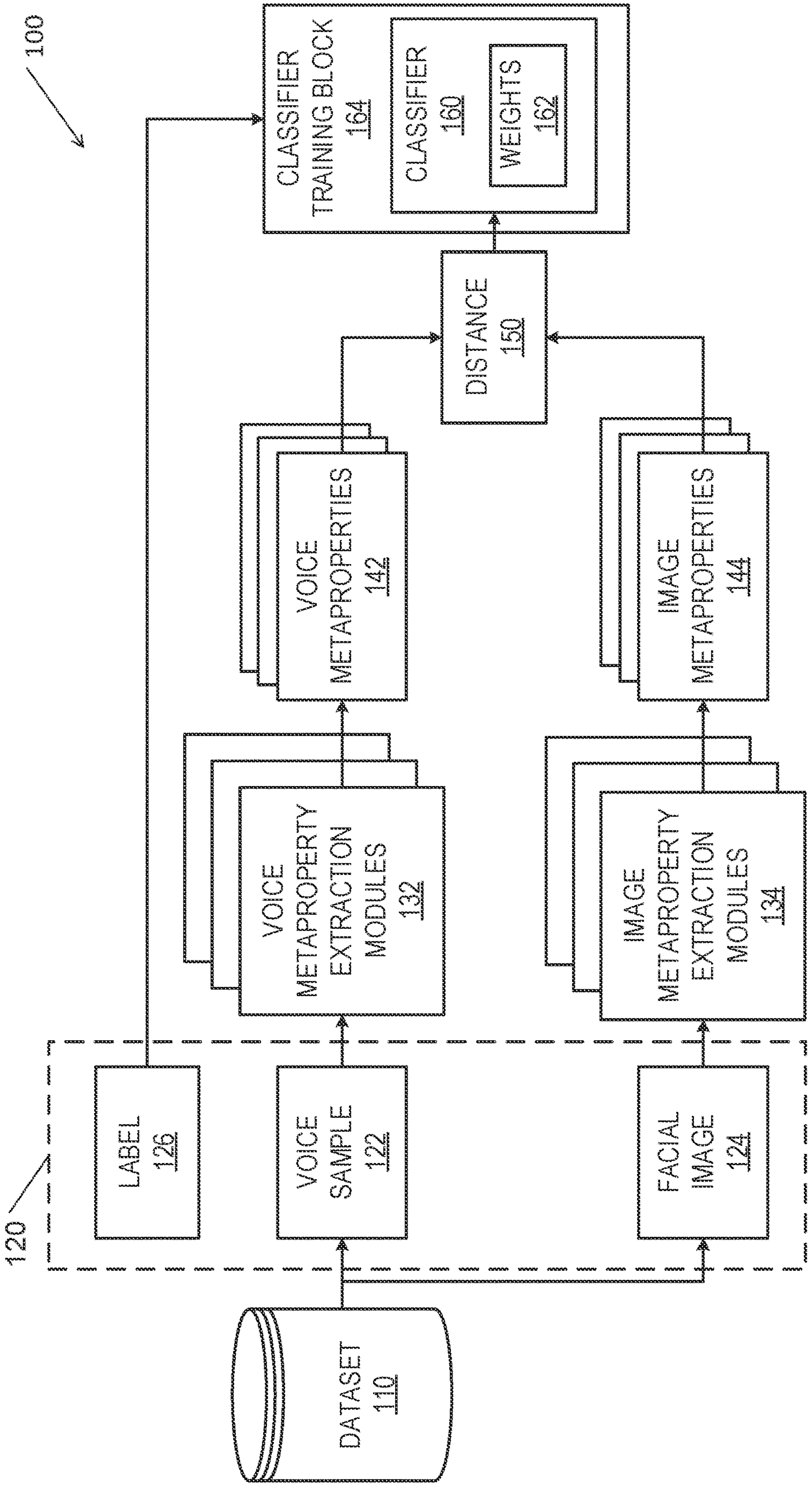
100
120
DATASET
110
LABEL
126
VOICE
SAMPLE
122
FACIAL
IMAGE
124
VOICE
METAPROPERTY
EXTRACTION
MODULES
132
IMAGE
METAPROPERTY
EXTRACTION
MODULES
134
VOICE
METAPROPERTIES
142
IMAGE
METAPROPERTIES
144
DISTANCE
150
CLASSIFIER
TRAINING BLOCK
164
CLASSIFIER
160
WEIGHTS
162

Fig. 1

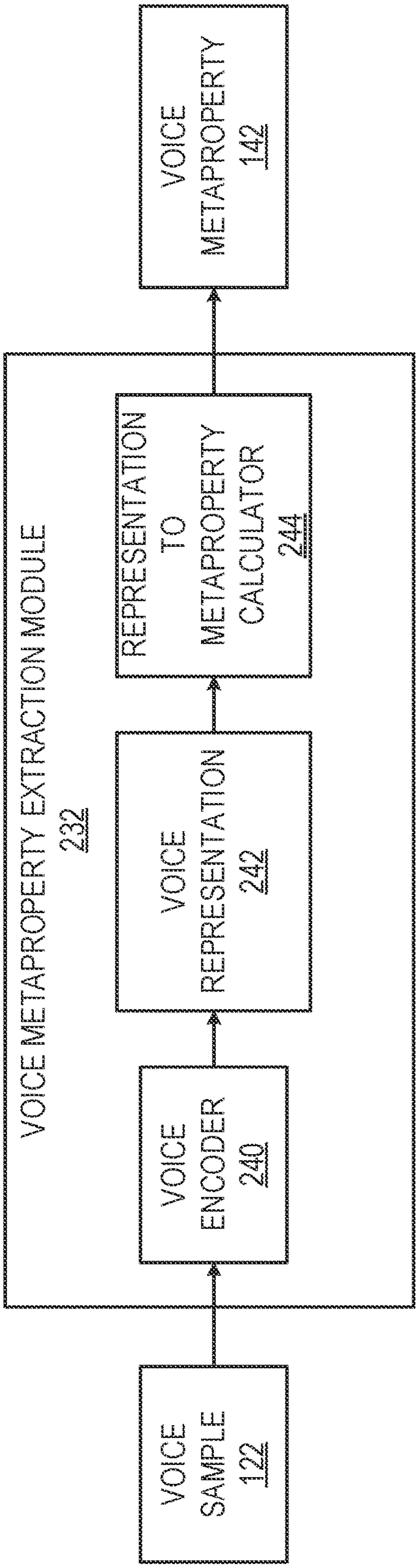
VOICE SAMPLE 122
VOICE METAPROPERTY EXTRACTION MODULE 232
VOICE ENCODER 240
VOICE REPRESENTATION 242
REPRESENTATION TO METAPROPERTY CALCULATOR 244
VOICE METAPROPERTY 142

Fig. 2A

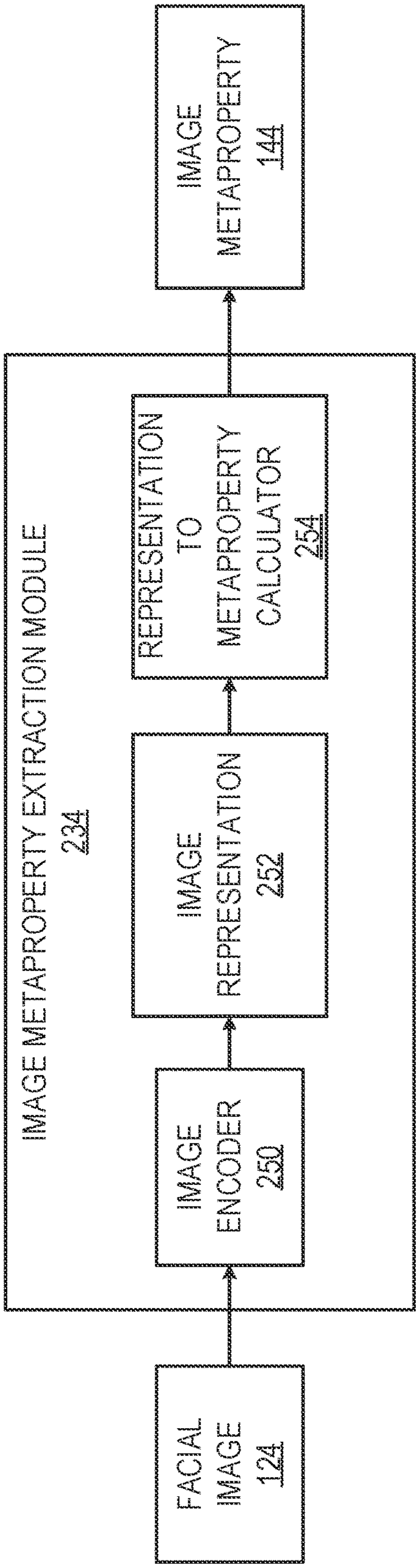
FACIAL IMAGE 124
IMAGE METAPROPERTY EXTRACTION MODULE 234
IMAGE ENCODER 250
IMAGE REPRESENTATION 252
REPRESENTATION TO METAPROPERTY CALCULATOR 254
IMAGE METAPROPERTY 144

Fig. 2B

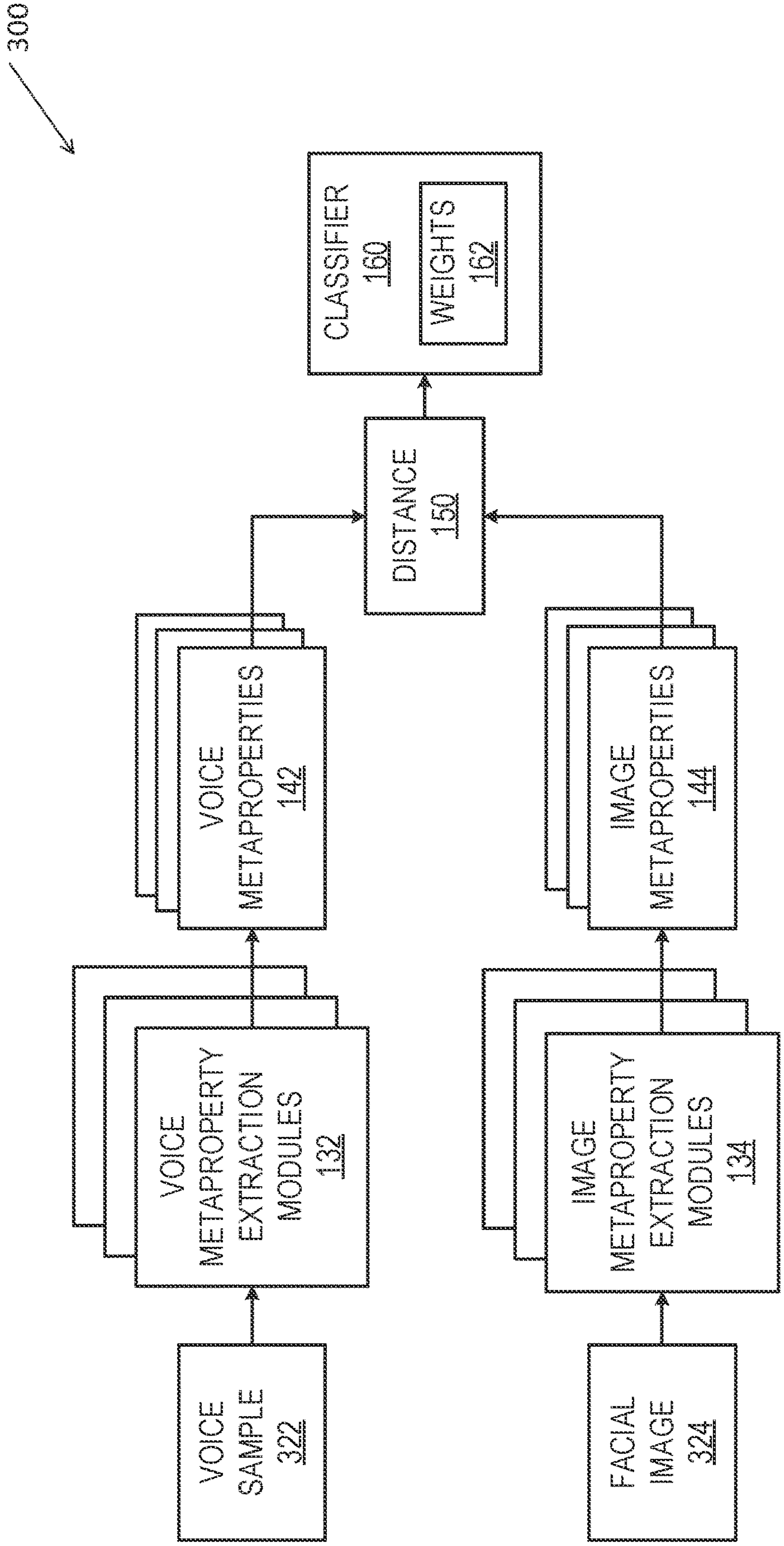
300
VOICE SAMPLE 322
VOICE METAPROPERTY EXTRACTION MODULES 132
VOICE METAPROPERTIES 142
DISTANCE 150
CLASSIFIER 160
WEIGHTS 162
FACIAL IMAGE 324
IMAGE METAPROPERTY EXTRACTION MODULES 134
IMAGE METAPROPERTIES 144

Fig. 3

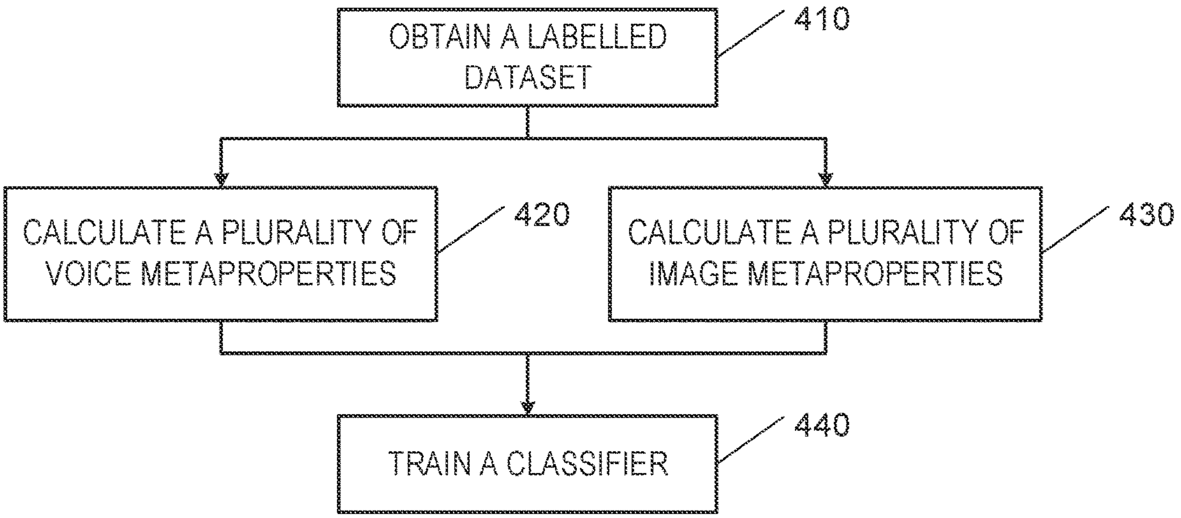
OBTAIN A LABELLED DATASET
410
CALCULATE A PLURALITY OF VOICE METAPROPERTIES
420
CALCULATE A PLURALITY OF IMAGE METAPROPERTIES
430
TRAIN A CLASSIFIER
440

Fig. 4

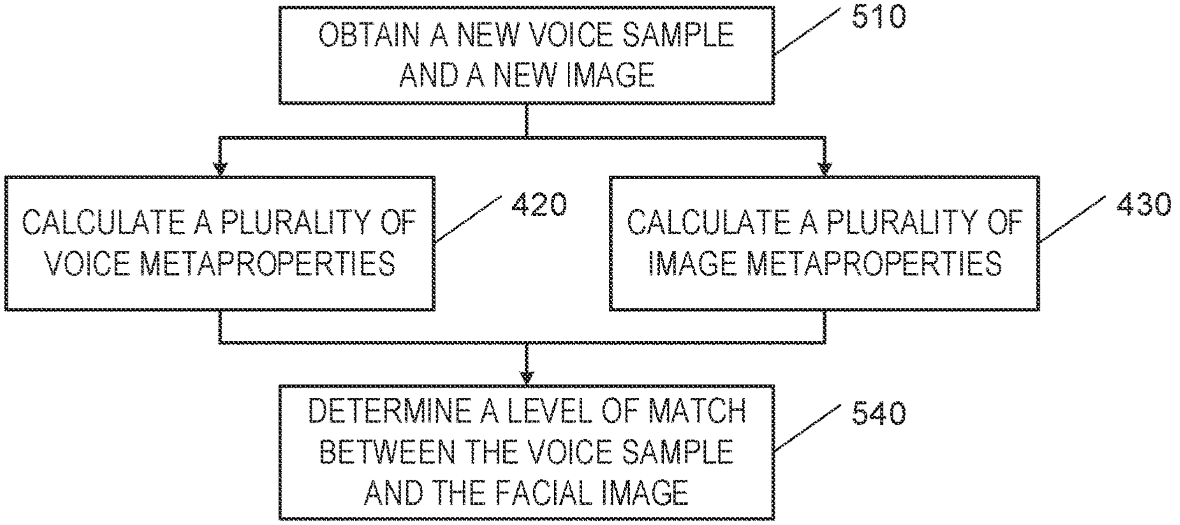
OBTAIN A NEW VOICE SAMPLE AND A NEW IMAGE
510
CALCULATE A PLURALITY OF VOICE METAPROPERTIES
420
CALCULATE A PLURALITY OF IMAGE METAPROPERTIES
430
DETERMINE A LEVEL OF MATCH BETWEEN THE VOICE SAMPLE AND THE FACIAL IMAGE
540

Fig. 5

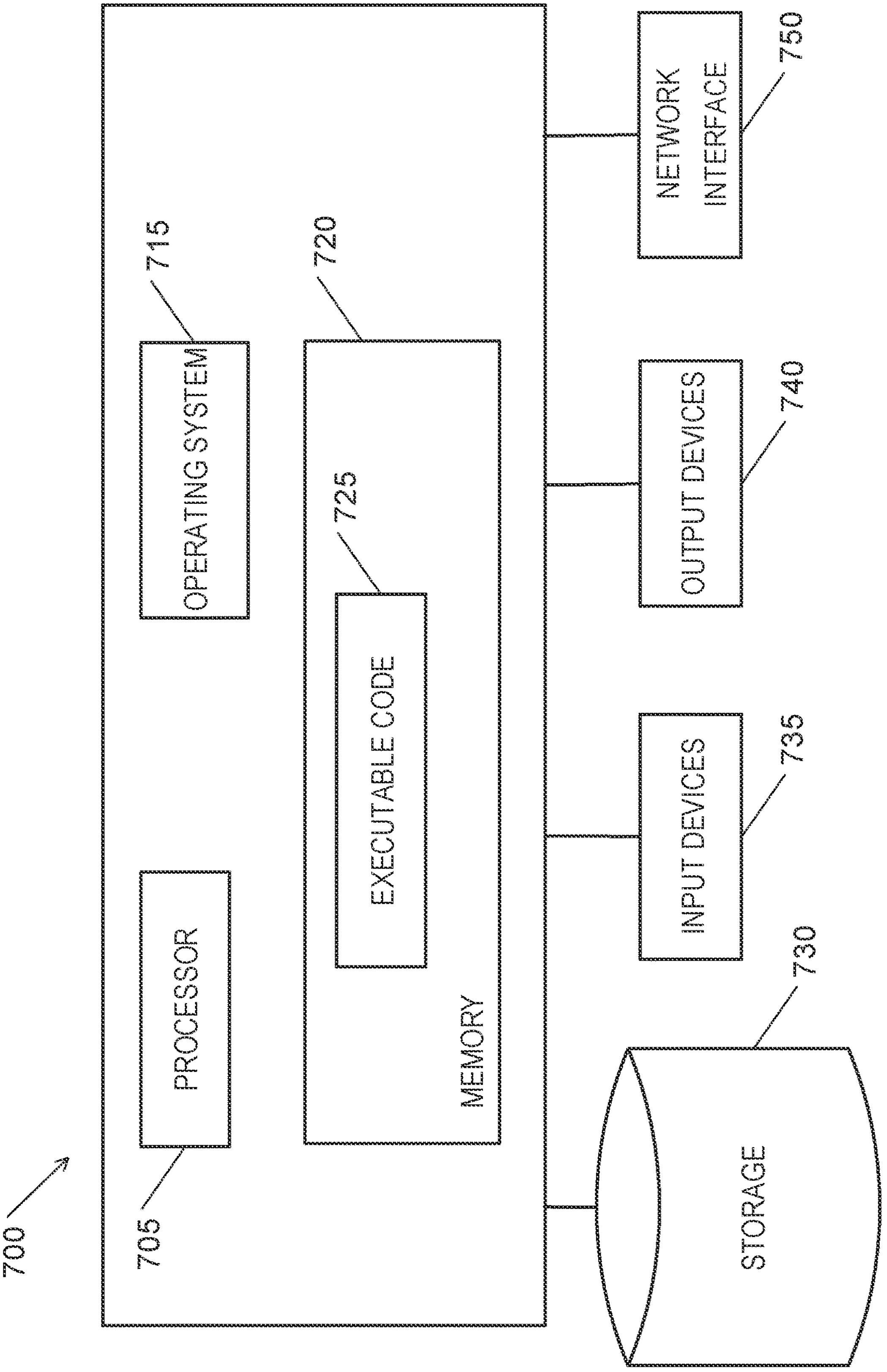
700
705
PROCESSOR
715
OPERATING SYSTEM
720
725
EXECUTABLE CODE
MEMORY
730
STORAGE
735
INPUT DEVICES
740
OUTPUT DEVICES
750
NETWORK INTERFACE

Fig 6

SYSTEM AND METHOD FOR MATCHING A VOICE SAMPLE TO A FACIAL IMAGE BASED ON VOICE AND IMAGE METAPROPERTIES

FIELD OF THE INVENTION

The present invention relates generally to matching a voice sample to a facial image; by way of non-limiting example, a voice sample may be matched to a facial image or vice versa based on voice and image metaproperties.

BACKGROUND

It has been shown experimentally that human appearances are associated with their voices. For example, properties like age, gender, ethnicity, and accent may influence both the facial appearance and the voice. In addition, there exist other, more subtle properties that influence both the facial appearance and voice, such as the level of specific hormones.

Voice face matching problems may be defined by the following task: provided with a sample of a person's voice and a plurality of images of a plurality of persons, determine which face belongs to the speaker.

Current solutions to the voice face matching problem typically require training machine learning (ML) models to generate embeddings of the voice samples and facial images. Voice-face matching, e.g., the likelihood that a voice sample matches a facial image and both originate from the same person, may be determined based on the distance between the latent vectors.

SUMMARY

According to embodiments of the invention, a computer-based system and method for matching a voice sample to a facial image may include, using a processor: obtaining a voice sample and a facial image; calculating a plurality of voice metaproperties from the voice sample; calculating a plurality of image metaproperties from image sample, where each of the image metaproperties corresponds to one of the voice metaproperties; and determining a level of match between the voice sample and the facial image, based on the plurality of voice metaproperties and the plurality of image metaproperties.

According to some embodiments of the invention, each of the voice metaproperties and the image metaproperties may include a probability distribution providing the probabilities that the voice metaproperty or the image metaproperty equals certain values of the metaproperty.

According to some embodiments of the invention, determining whether the voice sample matches the facial image may include: calculating a distance between each of the voice metaproperties and the corresponding image metaproperty; calculating a weighted sum of the distances; and determining that the voice sample matches the facial image if the weighted sum satisfies a threshold condition, and that the voice sample does not match the facial image otherwise.

According to some embodiments of the invention, calculating weights for the weighted sum operation may be done by training a classifier and deriving the weights from the parameters of the classifier.

According to some embodiments of the invention, the classifier may be a binary classifier.

According to some embodiments of the invention, the classifier may be trained by: obtaining a labelled dataset comprising a plurality of matching pairs labelled as matching pairs, and a plurality of unmatching pairs, labelled as unmatching pairs, where each of the matching pairs comprises a matching labelled voice sample and labelled facial image, and each of the unmatching pairs comprises an unmatching labelled voice sample and labelled facial image; calculating, for each of the labelled voice samples, the plurality of voice metaproperties from the labelled voice sample; calculating, for each of the labelled facial images, the plurality of image metaproperties from the labelled facial image; and using the plurality of voice metaproperties and the plurality of image metaproperties of the plurality of matching pairs and the plurality of unmatching pairs, and the associated labels, to train the classifier.

According to some embodiments of the invention, calculating one voice metaproperty of the plurality of voice metaproperties may include: encoding the voice sample into a voice representation using a voice encoder; and calculating the vector of voice metaproperties from the voice representation; and where calculating one image metaproperty of the plurality of image metaproperties comprises: encoding the facial image into an image representation using a face encoder; and calculating a vector of image metaproperties from image representation.

According to some embodiments of the invention, each of the metaproperties may include an identity characteristic of an individual.

According to some embodiments of the invention, the metaproperties may include at least one property selected from: age, gender, weight, body mass index (BMI), skin tone, mother tongue and accent.

Embodiments of the invention may include obtaining a plurality of facial images; determining a level of match between the voice sample and each the facial images; selecting the facial images with a highest level of match; and reconstructing the face of the speaker in the voice sample by fusing the selected facial images.

BRIEF DESCRIPTION OF THE DRAWINGS

Non-limiting examples of embodiments of the disclosure are described below with reference to figures attached hereto that are listed following this paragraph. Dimensions of features shown in the figures are chosen for convenience and clarity of presentation and are not necessarily shown to scale.

The subject matter regarded as the invention is particularly pointed out and distinctly claimed in the concluding portion of the specification. The invention, however, both as to organization and method of operation, together with objects, features and advantages thereof, can be understood by reference to the following detailed description when read with the accompanying drawings. Embodiments of the invention are illustrated by way of example and not limitation in the figures of the accompanying drawings, in which like reference numerals indicate corresponding, analogous or similar elements, and in which:

FIG. 1 depicts a system for training voice-face matching classifier, according to embodiment of the invention.

FIG. 2A depicts a voice metaproperty extraction module, according to embodiment of the invention.

FIG. 2B depicts an image metaproperty extraction module, according to embodiment of the invention.

FIG. 3 depicts a system for voice-face matching using a trained classifier, according to embodiment of the invention.

FIG. **4** is a flowchart of a method for training a classifier for voice-face matching, according to embodiments of the invention.

FIG. **5** is a flowchart of a method for matching a voice sample to a facial image using a trained classifier, according to embodiments of the invention.

FIG. **6** shows a high-level block diagram of an exemplary computing device which may be used with embodiments of the present invention.

It will be appreciated that for simplicity and clarity of illustration, elements shown in the figures have not necessarily been drawn accurately or to scale. For example, the dimensions of some of the elements can be exaggerated relative to other elements for clarity, or several physical components can be included in one functional block or element.

DETAILED DESCRIPTION

In the following detailed description, numerous specific details are set forth in order to provide a thorough understanding of the invention. However, it will be understood by those skilled in the art that the present invention can be practiced without these specific details. In other instances, well-known methods, procedures, and components, modules, units and/or circuits have not been described in detail so as not to obscure the invention.

Prior art solutions to the voice face matching problem typically require training ML models to generate embeddings of the voice samples and facial images. The ML models, typically deep leaning neural networks, may be trained so that the distance between latent vectors of voices and faces that originate from the same person will be smaller than the distance between latent vectors of voices and faces that originate from two different persons. Thus, voice-face matching, e.g., the likelihood that a voice sample matches a facial image, and both originate from the same person, may be determined based on the distance between the latent vectors.

ML based solutions as described above may have some significant drawbacks in terms of explainability, accuracy, precision, recall, scalability and cost effectiveness. Deep learning models may be challenging to comprehend. Due to the convoluted architecture of the models that typically involve plethora of parameters and hyper-parameters, it is often highly challenging to understand the reason why a given audio sample is matched or is not matched by the network to a specific face. It is also hard to tell in advance which faces will be easier or harder to match to an audio sample (e.g., with higher or lower chances to succeed). Even worse, if a prediction of the model is wrong, it may be unclear what causes the fault and how it can be fixed. Sources for erroneous matching by an ML model may include bias in data used for training the model, suboptimal selection of hyper-parameters, over fitting of the ML model, and more. However, when faced with low success rate, it is hard or impossible to know which of all those causes is the source of the problem, which can lead to difficulties in debugging and in increasing the system accuracy, precision and recall.

Prior art ML based systems may also have the problem of low generalizability. It is natural to fine-tune existing models (once trained) when their performance drops due to the addition of many new people of interest (POIs), e.g., people with characteristics that the ML model was not initially trained for. For example, if the ML model has been trained to match faces and voices of adults, it may have to be retrained to match voices and faces of adolescents. Every such retraining may require a long and tedious adjustments of hyper-parameters, where each fine tuning may take a large period of time and incur considerable costs. Thus, maintenance and generalization of such models may be complex and costly.

Last and foremost, deep ML models for voice-face matching may be inaccurate even if the audio and faces are encoded using state-of-the-art (SOTA) embeddings. Training deep ML models often overfits the data and the general accuracy of such models may not be sufficient to tell one person from another.

Embodiments of the invention may provide a system and method for matching or correlating a voice sample to a facial image. Embodiments of the invention may match a voice sample to a facial image based on corresponding metaproperties extracted from the voice sample and the facial image. A metaproperty, also referred to as metadatum, may include an identity characteristic of the individual whose voice is recorded in the voice sample or whose face is captured in the facial image, such as age, gender, weight, body mass index (BMI), skin tone, mother tongue, accent, etc. In some embodiments, the voice metaproperties and the image metaproperties may include a probability distribution providing the probabilities that the voice metaproperty or the image metaproperty equals certain values of the metaproperty. Thus, embodiments of the invention may extract or estimate a value, a value range, or a probability distribution, of a metaproperty, e.g., age, from a voice sample, and extract the same metaproperty from a facial image, and may repeat this process for a plurality of metaproperties. Embodiments of the invention may determine a level of match between the voice sample and the facial image, based on the plurality of voice metaproperties and the plurality of image metaproperties, e.g., using a classifier.

For example, embodiments of the invention may determine a level of match between the voice sample and the facial image by calculating a distance between each of the voice metaproperties and the corresponding image metaproperty, calculating a weighted sum of the distances, and determining that the voice sample matches the facial image if the weighted sum satisfies a threshold condition, and that the voice sample does not match the facial image otherwise. According to some embodiments, the trainable parameters of the classifier may be the weights for the weighted sum, or may be used to extract or calculate the weights for the weighted sum. According to some embodiments, the weights for the weighted sum (e.g., the parameters of the classifier) operation may be calculated by training the classifier and adjusting its weights.

In some embodiments, the classifier may be trained using a labelled dataset including a plurality pairs of matching voice samples and facial images, labelled as matching pairs, and a plurality of pairs of unmatching voice samples and facial images, labelled as unmatching pairs by calculating a plurality of voice metaproperties for each of the voice samples in the matching and unmatching pairs, and a plurality of image metaproperties for each of the facial images in the matching and unmatching pairs, and using the plurality of voice metaproperties and the plurality of image metaproperties and the associated labels, to train the classifier.

Thus, embodiments of the invention may improve the technology of voice-face matching by providing a method that relies on voice and face metaproperties, instead of using a dedicated deep ML model. Embodiments of the invention may use ML models for extracting the metaproperties.

However, these ML models according to some embodiments of the invention may be much smaller and simpler than a deep ML model used for voice-face matching. In some cases, off-the-shelf or previously trained ML models may be used, for example, to extract an age or a gender from a voice sample or a facial image.

Embodiments of the invention may combine deep ML models and classical methods for associating a given voice with several approximate faces that have matching metaproperties. Embodiments of the invention may provide high levels of explainability of the results of the model since it may be possible to investigate the metaproperties and discover the possible sources of an error. Embodiments of the invention may provide easy generalization and high levels of flexibility since adding more metaproperties only requires adding modules for extracting those metaproperties from voice samples and facial images, and retraining the classifier to get new weights. Other modules of the system, e.g., modules that extract other metaproperties do not have to be retrained. Similarly, when adding new POIs with new characteristics, each module may be trained and tested separately, which may decrease the complexity of the training process and may increase the accuracy of the retrained system. Embodiments of the invention may increase the robustness to outliers in comparison to prior art systems, since each module of the system may be less affected by rare outliers.

Some practical applications examples of voice face matching may include criminal investigations where a sample of the voice is the only evidence: for example, the voice sample together with an image of a suspect may be provided to the system that may provide determination (and/or a confidence level) whether the voice and face belong to the same person or not. Another application may include deepfake speech synthesis detection, in which a fake audio is combined with a video of a person. In this case the audio may be provided together with an image of the talking person taken from the video, and the system may be provided to the system that may provide determination (and/or confidence level) whether the voice and face belong to the same person or not.

Embodiments of the invention may provide a probability that a speech sample and a face image match. Thus, embodiments of the invention may be used for, for example:

- Face database sorting-given a speech sample and a database of face photos, embodiments of the invention may be used to sort the database in order of probability that the person on the photo is the speech sample owner.
- Voice database sorting-given a photo of a person and a database of speech samples, embodiments of the invention may be used to sort the database in order of probability that the speech belongs to the person in the photo.
- Comparing probabilities-quantitatively comparing relative probabilities that a speech sample belongs to a first person rather than a second person.

According to embodiments of the invention, the voice and face encoders may include one or more neural networks (NN). NNs are computing systems inspired by biological computing systems, but operating using manufactured digital computing technology. NNs are mathematical models of systems made up of computing units typically called neurons (which are artificial neurons or nodes, as opposed to biological neurons) communicating with each other via connections, links or edges. In common NN implementations, the signal at the link between artificial neurons or nodes can be for example a real number, and the output of each neuron or node can be computed by function of the (typically weighted) sum of its inputs, such as a rectified linear unit (ReLU) function. NN links or edges typically have a weight that adjusts as learning or training proceeds typically using a loss function. The weight increases or decreases the strength of the signal at a connection. Typically, NN neurons or nodes are divided or arranged into layers, where different layers can perform different kinds of transformations on their inputs and can have different patterns of connections with other layers. NN systems can learn to perform tasks by considering example input data, generally without being programmed with any task-specific rules, being presented with the correct output for the data, and self-correcting, or learning using a loss function.

Some embodiments of the invention may include other deep architectures such as transformers, that may include series of layers of self-attention mechanisms and feedforward neural networks, used for processing input data. Transformers may be used in light of their capacity of parallelism and their multi-headed self-attention which facilitate features extraction.

Various types of NNs exist. For example, a convolutional neural network (CNN) can be a deep, feed-forward network, which includes one or more convolutional layers, fully connected layers, and/or pooling layers. CNNs are particularly useful for visual applications. Other NNs can include for example time delay neural network (TDNN) which is a multilayer artificial neural network that can be trained with shift-invariance in the coordinate space.

In practice, an NN, or NN learning, may be performed by one or more computing nodes or cores, such as generic central processing units or processors (CPUs, e.g. as embodied in personal computers), graphics processing units (GPUs), or tensor processing units (TPUs). which can be connected by a data network.

The facial images may be provided in any applicable computerized image format such as joint photographic experts group (JPEG or JPG), portable network graphics (PNG), graphics interchange format (GIF), tagged image file (TIFF), etc., and the voice or speech sample may be provided in any applicable computerized audio format such as MP3, MP4, M4A, WAV, etc.

The voice samples and facial images may be provided to one or more voice or image encoders (e.g., NNs), that may each generate an embedding, e.g., a latent space vector, also referred to herein simply as a latent vector, a latent matrix, a signature or a feature vector, in a feed forward process, for each of the voice and images. As used herein, an embedding may include a reduced dimension (e.g., compressed) representation of the original data, generated for example by an ML model or an encoder. The embedding may include a vector (e.g., an ordered list of values) or a matrix that represents the original data in a compressed form that, if generated properly, includes important or significant components or characteristics of the raw data. Embodiments of the invention may use embedding to extract metaproperties, where different embedding may be generated for different metaproperties.

Reference is made to FIG. **1**, which depicts a system **100** for training voice-face matching classifier **160**, according to embodiment of the invention. It should be understood in advance that the components and functions shown in FIG. **1** are intended to be illustrative only and embodiments of the invention are not limited thereto. While in some embodiments of the system of FIG. **1** are implemented using systems as shown in FIG. **6**, in other embodiments other systems and equipment can be used.

Dataset **110** may include labelled pairs **120** of matching and unmatching voice samples **122**, also referred to as speech samples) and facial images **124**, e.g., voice samples **122** and facial images **124** of the same person or of different persons, respectively. Dataset **110** may be stored, for example, on storage **730** presented in FIG. **6**. Pair **120** may be labelled by label **126** indicative whether pair **120** includes matching or unmatching voice samples **122** and facial images **124**. In some embodiments, dataset **110** may include a face dataset including facial images and an audio dataset including audio recordings. Each of the facial images and audio recordings may be associated with metadata including speaker identification numbers (IDs) and ground truth values of the meta-properties. A facial image and an audio recording may be matched into pair **120** based on the speaker IDs, e.g., a facial image and an audio recording having the same speaker IDs may be matched and provided with a label **126** indicating that the facial image and audio recording are of the same person, and a facial image and an audio recording having different speaker IDs may be matched and provided with a label **126** indicating that the facial image and audio recording are not of the same person.

Each of voice metaproperty extraction modules **132** may be configured to estimate, calculate or extract a voice metaproperty **142** from a voice sample **122**. Each of voice metaproperties **142** may include an identity characteristic of the person speaking in voice sample **122** such as the age, gender, weight, body mass index (BMI), skin tone, mother tongue, accent of the person speaking. Some voice metaproperties **142** may be estimated, calculated or extracted directly from voice sample **122**, while other may include an intermediate stage of extracting or calculating a voice representation **242**, using, for example, an ML voice encoder **240**, and extracting, estimating or calculating voice metaproperty **142** from voice representation **242**, e.g., as depicted in FIG. **2**A. For some voice metaproperties **142**, voice representation **242** may include a voice latent vector, a voice latent matrix or an embedding. For some voice metaproperties **142**, voice representation **242** may include a representation of the voice in the form of one or more matrices or an image, e.g., a spectrogram, or a red channel matrix, a green channel matrix and a blue channel matrix, or other matrices or images that are calculated based on voice sample **122** by voice encoder **240**. Other representations may be used.

Similarly, each of image metaproperty extraction modules **134** may be configured to estimate, calculate or extract an image metaproperty **144** from a facial image **124**. Each of image metaproperties **144** may include an identity characteristic of the person whose face is depicted in facial image **124** as the age, gender, weight, body mass index (BMI), skin tone, mother tongue, accent etc. Some image metaproperties **144** may be estimated, calculated or extracted directly from facial image **124**, while other may include an intermediate stage of extracting or calculating an image representation **252**, using, for example, an ML image encoder **250**, and extracting, estimating or calculating image metaproperty **144** from the image representation **252**, e.g., as depicted in FIG. **2**B. For some image metaproperties **144**, image representation **252** may include an image latent vector, an image latent matrix or an embedding. Other representations may be used.

FIG. **2**A depicts a voice metaproperty extraction module **232**, according to embodiments of the invention. Voice metaproperty extraction module **232** is one possible implementation of voice metaproperty extraction module **132** in which a voice representation **242** is extracted or calculated by ML voice encoder **240**, and voice metaproperty **142** is extracted, estimated or calculated from voice representation **242** by representation to metaproperty calculator **244**. Voice encoder **240** may include an ML model, such as an NN that may generate an embedding, a speech signature, a latent vector, a latent matrix, a spectrogram or other image representation of voice sample **122**. Representation to metaproperty calculator **244** may perform any calculations required to extract, estimate or calculate a voice metaproperty **142** from a voice representation **242**, including but not limited to a classical ML model, e.g., linear regression, logistic regression, support vector machines, nearest neighbor similarity search, decision trees, etc., or a deep ML model e.g., any applicable type of deep NN. It is noted that system **100** may include a plurality of types of voice encoders **240**, each for a different voice metaproperty **142**. For example, one voice encoder **240** may be used for generating a voice representation **242**, e.g., a latent vector, that may be used for calculating voice age metaproperty, while another different voice encoder **240** may be used for generating a second representation vector **242**, e.g., a spectrogram, that may be used for calculating audio gender metaproperty, etc. Other implementations of voice metaproperty extraction module **132** may be used.

FIG. **2**B depicts an image metaproperty extraction module **234**, according to embodiments of the invention. Image metaproperty extraction module **234** is one possible implementation of image metaproperty extraction module **134** in which an image representation **252** is extracted or calculated by ML image encoder **250**, and image metaproperty **144** is extracted, estimated or calculated from image representation **252** by representation to metaproperty calculator **254**. Image encoder **250** may include an ML model, such as an NN that may generate a representation such as a latent vector (e.g., face signature vectors) for facial image **124**. Representation to metaproperty calculator **254** may perform any calculations required to extract, estimate or calculate an image metaproperty **144** from an image representation **252**, including but not limited to a classical ML model, e.g., linear regression, logistic regression, support vector machines, nearest neighbor similarity search, decision trees, etc., or a deep ML model e.g., any applicable type of deep NN. It is noted that system **100** may include a plurality of types of image encoders **250**, each for a different image metaproperty **144**. For example, one image encoder **250** may be used for generating an image representation **252**, e.g., a latent vector, that may be used for calculating image age metaproperty, while another image encoder **250** may be used for generating a second image representation **252**, e.g., a latent matrix, that may be used for calculating image gender metaproperty, etc. Other implementations of image metaproperty extraction module **134** may be used.

Some voice metaproperties **142** and image metaproperties **144** may be categorical features, e.g., gender (at birth), while others may be continuous features, e.g., age. Some continuous features may be treated as categorical features, by dividing the entire range of possible values into sub-ranges where voice metaproperties **142** and image metaproperties **144** may include the sub-range, e.g., age of 24-32. It is noted that discretization of continuous categories may be done to ranges of varying sizes (e.g. in table 1 an age range of 18-19, which is 2 years vs. age range of 33-40 which is 7 years). Some of voice metaproperties **142** and image metaproperties **144** may include a probability distribution providing the probabilities that the voice metaproperty **142** or the image metaproperty **144** equals certain values or ranges of values of the metaproperty. An example of an age voice metaproperty (extracted from voice sample **122**) is provided in Table 1. In the example of Table 1, the age is divided to the sub-ranges of under 18, 18-19, 20-24, 25-32, 33-40, 41-48, 49-56, 57-64 and over 64 years old. The result of voice metaproperty extraction modules **132** may include the probabilities that the age of the speaker is in the specified age range. Table 2 provides a similar example for gender metaproperty. In this example there are only two possible values, e.g., male and female, and the result of voice metaproperty extraction modules **132** may include the probabilities that the speaker is either male or female. Similar types or categories of metaproperties may be calculated by image metaproperty extraction modules **134** from facial image **124**, with possible different values.

TABLE 1

An example of age voice metaproperty values

Value	<18	18-19	20-24	25-32	33-40	41-48	49-56	57-64	>64
Probability	0	0	0.15	0.55	0.24	0.06	0	0	0

TABLE 2

An example of gender metaproperty values

Value	Male	Female
Probability	0.85	0.15

In some embodiments, the types of image metaproperties **144** may correspond to the types of voice metaproperties **142**, for example, a voice age metaproperty may be extracted from voice sample **122** and an image age metaproperty may be extracted from facial image **124**. Thus, a specific image metaproperty may correspond to a specific voice metaproperty if both metaproperties are of the same or corresponding type. Similarly, other types of metaproperties may be calculated once from voice sample **122** and once from facial image **124**.

In some embodiments, the metaproperties may include:

Gender [male, Female]:

a voice gender metaproperty may be generated by extracting a voice latent vector from voice sample **122** using a voice encoder, and feeding the voice latent vector into a classical ML model trained to calculate probability distribution providing the probabilities that the speaker is a male or a female. The voice encoder, the voice latent vector and the classical ML model may be specific for the voice gender metaproperty.

an image gender metaproperty may be generated by extracting an image latent vector from facial image **124** using an image encoder and feeding the image latent vector into a classical ML model trained to calculate probability distribution providing the probabilities that the person depicted in the image is a male or a female. The image encoder, the image latent vector and the classical ML model may be specific for the image gender metaproperty.

Age [age ranges in years]:

a voice age metaproperty may be generated by extracting a voice latent vector from voice sample **122** using a voice encoder, and feeding the voice latent vector into a deep ML model trained to calculate probability distribution providing the probabilities that the speaker age is in each of the age ranges. The voice encoder, the voice latent vector, and deep ML model may be specific for the age gender metaproperty.

an image age metaproperty may be generated by providing facial image **124** directly into a deep ML model trained to calculate probability distribution providing the probabilities that the age of the person depicted in the image is in each of the age ranges. The deep ML model may be specific for the image age metaproperty.

Skin tone [e.g., according to the Fitzpatrick scale]

a categorial feature predicted on the Fitzpatrick scale having 6 possible skin tone categories ranging from types I to VI, where type I may refer to a skin tone that always burns, while type VI may refer to a skin tone that never burns. in some embodiments, each of the image and voice skin tone metaproperties may be extracted using a classifier or deep ML model (e.g., an NN, CNN, transformer or an auto-encoder). In some embodiments, the image skin tone metaproperty may be extracted or predicted by feeding facial image **124** into a transformer, e.g. a vision transformer, and the voice skin tone metaproperty may be extracted by generating a latent matrix e.g. in the form of a Mel spectrogram and performing predictions on the latent matrix using transformers, e.g. a vision transformer. Other scales and/or methods may be used.

Ethnicity [Asian, Black, White, Middle-Eastern, Indian, Latino Hispanic]

Each of the age and voice ethnicity metaproperties may be extracted, for example, using a classifier or deep ML model (e.g., an NN, CNN, transformer or an auto-encoder). Other models may be used.

Weight, measures in kilograms. Attains non-negative values.

Body Mass Index (BMI)

Mother tongue.

Accent.

Returning to FIG. **1**, voice metaproperties **142** and image metaproperties **144** may be fed into distance calculator **150**, that may calculate a distance, e.g., Euclidean distance, cosine distance (e.g., equals one minus cosine similarity) or other measures of distance, between each of voice metaproperties **142** and its corresponding image metaproperty **144**, e.g., between the audio gender metaproperty and the image gender metaproperty, between the audio age metaproperty and the image age metaproperty, etc. It is noted that other relationships between voice metaproperties **142** and image metaproperties **144** may be calculated by distance calculator **150**. The distances may be provided as distance vector d (e.g., an ordered list of the distances). Distance calculator **150** may further calculate a weighted sum of the distances (and/or the other relationships between voice metaproperties **142** and image metaproperties **144**) using weights **162**, e.g., by multiplying each distance value by a weight and adding the multiplications. The weighted sum may be provided to classifier **160** that may determine whether voice sample **122** matches facial image **124** (e.g., whether both originate from the same person) or not. For example, classifier **160** may determine whether voice sample **122** matches facial image **124** if the weighted sum satisfies a threshold condition (e.g., is higher than a threshold), and that voice sample **122** does not match facial image **124** otherwise. Other conditions may be used. Classifier training block **164** may use labels **126** and the classification provided by classifier **160** to train classifier

160. Weights **162** may be derived from the trainable parameters of classifier **160**, e.g., weights **162** may be the trainable parameters of classifier **160** or may be calculated using weights **162** . . . . Typically, equal number of random positive pairs (e.g., pairs of matching voice sample **122** and facial image **124**) and random negative pairs (e.g., pairs of unmatching voice sample **122** and facial image **124**) may be used for training, however this is not mandatory. For example, classifier training block **164** may train classifier **160** by adjusting weights **162** (that are derived from the trainable parameters of classifier **160**) of the weighted sum operation to minimize a loss function that measure the error between the know label **126** and the prediction of classifier **160**. In some embodiments classifier **160** may be a binary classifier, e.g., an ML algorithm that categorizes samples into one of two classes and allows weights extraction. Examples for a binary classifier may include a logistic regression classifier, an extreme gradient boosting (XGBoost) classifier, a random forest classifier, etc.

As noted, weights **162** used for the weighted sum operation of classifier **160** may be derived or calculated from the parameters or coefficients of classifier **160**. For example, in case a logistic regression classifier is used for classifier **160**, the weights may be the coefficients of the logistic regression, each multiplied by the standard deviation of the corresponding component. For example, in case of two metaproperties, gender and age, classifier **160** may be trained on vectors (gender_distance, age_distance), where gender_distance is a vector including the distances between the voice gender metaproperty and the corresponding image gender metaproperty of the samples used for training, and age_distance is the a vector including the distances between the voice age metaproperty and the corresponding image age metaproperty of the samples used for training. After training, a logistic regression with parameters beta_0, beta_1 and beta_2 is obtained. Thus, the weight of the gender metaproperty in this example would be beta_1×std_of_gender_distances and the weight of the age metaproperty would be beta_2×std_of_age_distances, where std_of_gender_distances and std_of_age_distances are the standard deviations of the gender_distance and age_distance vectors, respectively. Other ways for deriving the weights from the parameters of trained classifier **160** may be used.

According to some embodiments, classifier **160** may be initially trained with equal number of positive and negative pairs in order to avoid leaning towards positiveness or negativeness. Thereafter, weighted training may be applied as described infra. A distance vector d may be calculated for pair **120**, and classifier **160** may predict that pair **120** is a positive pair (e.g., that the voice sample and the facial image in pair **120** match or originate from the same person) in probability p. A confidence level c (d) may be calculated by, for example:

$$c(d)=\max(p,1-p)$$

I. The ground truth label may be denoted as y_{true}(d), and the predicted label may be denoted as y_{pred}(d). Two thresholds may be used ε_{strong}, $\varepsilon_{weak} \in [0.5,1]$, and the distance vector d may be categorised as hard, medium and easy according to: Hard—the prediction of the model is wrong with high confidence level:

$$\begin{cases} y_{pred(d)} \neq y_{true}(d) \\ c(d) > \varepsilon_{strong} \end{cases}$$

II. Medium—the prediction of the model is right or wrong with medium confidence level:

$$\begin{cases} y_{pred(d)} \neq y_{true}(d) \\ \varepsilon_{weak} < c(d) > \varepsilon_{strong} \end{cases}$$

III. Easy—the prediction of the model is correct with high confidence level:

$$\begin{cases} y_{pred(d)} = y_{true}(d) \\ c(d) > \varepsilon_{strong} \end{cases}$$

The categorization of the weighted sum d may allow retraining classifier **160** in different manners, for example:

Curriculum learning-ordering pairs **120** in increasing difficulty, first easy, then medium and lastly hard. A known phenomenon in biology called 'shaping' implies that animal brains learn quicker when the learning is done gradually from easier to harder examples alluding to more complex and richer concepts in the data. This phenomenon can be transferred to machine learning, e.g., after ordering pairs **120** in increasing difficulty classifier **160** may be trained gradually starting from the easy, then medium and lastly hard pairs **120**.

Learning through difficulty-adjusted weights-giving the lowest effect on the training process (e.g., the lowest effect on adjusting weights **162**) for pairs **120** categorised as easy, higher effect on adjusting weights **162** for pairs **120** categorised as medium, and the highest effect on adjusting weights **162** for pairs **120** categorised as hard.

Not using pairs **120** categorised as easy and pairs **120** categorised as hard in the training process, since pairs **120** that are categorised as easy may not contribute much to the training process and pairs **120** categorised as hard may be too challenging for the model training. This method may result in different number of positive and negative pairs **120**.

Other methods for training classifier **160** may be used.

Reference is made to FIG. **3**, which depicts a system **300** for voice-face matching using a trained classifier **160**, according to embodiment of the invention. It should be understood in advance that the components and functions shown in FIG. **3** are intended to be illustrative only and embodiments of the invention are not limited thereto. While in some embodiments the system of FIG. **3** is implemented using systems as shown in FIG. **6**, in other embodiments other systems and equipment can be used.

System **300** may obtain a new voice sample **322** and a new facial image **324**. New in this context implies that new voice sample **322** and a new facial image **324** are not labelled and system **300** does not know in advance whether new voice sample **322** and new facial image **324** match or not. Voice metaproperty extraction modules **132** may extract voice metaproperties **142**, image metaproperty extraction modules **134** may extract image metaproperties **144**, and distance calculator **150** may calculate distances or other relations between voice metaproperties **142** and their corresponding image metaproperties **144**, similarly to system **100**. Classifier **162** may use the trained weights **162**, to calculate a weighted sum of the distances and may provide, based on the weighted sum of the distances, a determination whether new voice sample **322** and a new facial image **324** match or not, or a level of match between the voice sample and the facial image. For example, the level of match may equal the weighted sum and the determination may be provided by testing the level of match against a threshold, e.g., classifier **160** may determine that new voice sample **322** matches new facial image **324** if the weighted sum satisfies a threshold condition, and that new voice sample **322** does not match new facial image **324** otherwise.

According to some embodiments, system **300** may be used for reconstructing a facial image of a specker by, for example, obtaining a voice sample **322** or the specker and a plurality of facial images **324**, determining a level of match between voice sample **322** and each of facial images **324**, selecting the facial images with the highest level of match, and reconstructing the face of the speaker in voice sample **322** by fusing the selected facial images. Selecting the facial images with the highest level of match may include, for example, selecting facial images with a level of match that satisfies (e.g., that is higher than) a threshold, selecting a predetermined number N or a predetermined percentage P of facial images with the highest level of match. For example, the plurality of facial images **324** may be ordered according to their level of match, and the top N ranked facial images or the top P percentage of facial images may be selected.

Reference is now made to FIG. **4**, which is a flowchart of a method for training a classifier for voice-face matching, according to embodiments of the invention. While in some embodiments the operations of FIG. **4** are carried out using systems as shown in FIGS. **1** and **6**, in other embodiments other systems and equipment can be used.

In operation **410**, a processor (e.g., processor **705** depicted in FIG. **6**), may obtain a labelled dataset including a plurality of matching pairs labelled as matching pairs, and including a matching voice sample and facial image, and a plurality of unmatching pairs, labelled as unmatching pairs, and including an unmatching voice sample and facial image. In operation **420**, the processor may calculate a plurality of voice metaproperties for each of the voice samples, as disclose herein. In operation **430**, the processor may calculate a plurality of image metaproperties for each of the images, as disclose herein. In operation **440**, the processor may use the plurality of voice metaproperties and the plurality of image metaproperties of the plurality of matching pairs and the plurality of unmatching pairs, and the associated labels, to train the classifier. For example, the processor may calculate distances between corresponding voice metaproperties and image metaproperties, and a weighted sum of those distances, and may train the classifier by adjusting the trainable parameters of the classifier which are the weights of the weighted sum operation, to minimize a loss function that measure the error between the know label and the prediction of the classifier.

Reference is now made to FIG. **5**, which is a flowchart of a method for matching a voice sample to a facial image using a trained classifier, according to embodiments of the invention. While in some embodiments the operations of FIG. **5** are carried out using systems as shown in FIGS. **3** and **6**, in other embodiments other systems and equipment can be used.

In operation **510**, a processor (e.g., processor **705** depicted in FIG. **6**), may obtain a voice sample and a facial image that are not labelled, e.g., processor **705** may not have prior knowledge on whether the voice sample and the facial image belong to the same person or not. In operation **420**, the processor may calculate a plurality of voice metaproperties for the voice sample and in operation **430** the processor may calculate a plurality of image metaproperties for the image, as disclose herein. In operation **540**, the processor may use the plurality of voice metaproperties and the plurality of image metaproperties to determine a level of match between the voice sample and the facial image. For example, the processor may provide the plurality of voice metaproperties and the plurality of image metaproperties to the classifier trained in operation **440**.

FIG. **6** shows a high-level block diagram of an exemplary computing device which may be used with embodiments of the present invention. Computing device **700** may include a controller or processor **705** that may be or include, for example, one or more CPUs, GPUs, TPUs and/or a chip or any suitable computing or computational device, an operating system **715**, a memory **720**, a storage **730**, input devices **735** and output devices **740**. Each of modules and equipment such as voice-face matching model **234** and loss calculation module **260**, as systems **100** and **200** shown in FIGS. **1** and **3**, respectively, or other modules described herein, may be executed by, a computing device such as included in FIG. **6** or specific components of FIG. **6**, although various units among these entities may be combined into one computing device.

Operating system **715** may be or may include any code segment designed and/or configured to perform tasks involving coordination, scheduling, supervising, controlling or otherwise managing operation of computing device **700**, for example, scheduling execution of programs. Memory **720** may be or may include, for example, a Random Access Memory (RAM), a read only memory (ROM), a Dynamic RAM (DRAM), a volatile memory, a non-volatile memory, a cache memory, or other suitable memory units or storage units. Memory **720** may be or may include a plurality of possibly different memory units. Memory **720** may store for example, instructions to carry out a method (e.g., code **725**), and/or data such as model weights, etc.

Executable code **725** may be any executable code, e.g., an application, a program, a process, task or script. Executable code **725** may be executed by processor **705** possibly under control of operating system **715**. For example, executable code **725** may when executed carry out methods according to embodiments of the present invention. For the various modules and functions described herein, one or more computing devices **700** or components of computing device **700** may be used. One or more processor(s) **705** may be configured to carry out embodiments of the present invention by for example executing software or code.

Storage **730** may be or may include, for example, a hard disk drive, a solid-state drive, a floppy disk drive, a Compact Disk (CD) drive, or other suitable removable and/or fixed storage unit. Data such as instructions, code, facial images, voice samples, training data, model weights and parameters etc. may be stored in a storage **730** and may be loaded from storage **730** into a memory **720** where it may be processed by processor **705**. Some of the components shown in FIG. **6** may be omitted.

Input devices **735** may be or may include for example a mouse, a keyboard, a touch screen or pad or any suitable input device. Any suitable number of input devices may be operatively connected to computing device **700** as shown by block **735**. Output devices **740** may include displays, speakers and/or any other suitable output devices. Any suitable number of output devices may be operatively connected to computing device **700** as shown by block **740**. Any applicable input/output (I/O) devices may be connected to computing device **700**, for example, a modem, printer or facsimile machine, a universal serial bus (USB) device or external hard drive may be included in input devices **735** or output devices **740**. Network interface **750** may enable device **700** to communicate with one or more other computers or networks. For example, network interface **750** may include a wired or wireless NIC.

Embodiments of the invention may include one or more article(s) (e.g. memory **720** or storage **730**) such as a computer or processor non-transitory readable medium, or a computer or processor non-transitory storage medium, such as for example a memory, a disk drive, or a USB flash memory, encoding, including or storing instructions, e.g., computer-executable instructions, which, when executed by a processor or controller, carry out methods disclosed herein.

One skilled in the art will realize the invention may be embodied in other specific forms using other details without departing from the spirit or essential characteristics thereof. The foregoing embodiments are therefore to be considered in all respects illustrative rather than limiting of the invention described herein. Scope of the invention is thus indicated by the appended claims, rather than by the foregoing description, and all changes that come within the meaning and range of equivalency of the claims are therefore intended to be embraced therein. In some cases well-known methods, procedures, and components, modules, units and/or circuits have not been described in detail so as not to obscure the invention. Some features or elements described with respect to one embodiment can be combined with features or elements described with respect to other embodiments.

Although embodiments of the invention are not limited in this regard, discussions utilizing terms such as, for example, "processing," "computing," "calculating," "determining," "establishing", "analyzing", "checking", or the like, can refer to operation(s) and/or process(es) of a computer, a computing platform, a computing system, or other electronic computing device, that manipulates and/or transforms data represented as physical (e.g., electronic) quantities within the computer's registers and/or memories into other data similarly represented as physical quantities within the computer's registers and/or memories or other information non-transitory storage medium that can store instructions to perform operations and/or processes.

Although embodiments of the invention are not limited in this regard, the terms "plurality" can include, for example, "multiple" or "two or more". The term set when used herein can include one or more items. Unless explicitly stated, the method embodiments described herein are not constrained to a particular order or sequence. Additionally, some of the described method embodiments or elements thereof can occur or be performed simultaneously, at the same point in time, or concurrently.

What is claimed is:

1. A method for matching a voice sample to a facial image, the method comprising, using a processor:

obtaining a voice sample and a facial image;

calculating a plurality of voice metaproperties from the voice sample;

calculating a plurality of image metaproperties from the facial image, wherein each of the image metaproperties corresponds to one of the voice metaproperties, wherein each of the voice metaproperties and the image metaproperties comprises a probability distribution providing the probabilities that the voice metaproperty or the image metaproperty equals certain values of the metaproperty; and

determining a level of match between the voice sample and the facial image, based on the plurality of voice metaproperties and the plurality of image metaproperties, wherein determining whether the voice sample matches the facial image is performed by:

calculating a distance between each of the voice metaproperties and the corresponding image metaproperty;

calculating weights for a weighted sum operation by training a classifier and deriving the weights from the parameters of the classifier;

calculating the weighted sum of the distances; and

determining that the voice sample matches the facial image if the weighted sum satisfies a threshold condition, and that the voice sample does not match the facial image otherwise,

wherein the classifier is trained by:

obtaining a labelled dataset comprising a plurality of matching pairs labelled as matching pairs, and a plurality of unmatching pairs, labelled as unmatching pairs, wherein each of the matching pairs comprises a matching labelled voice sample and labelled facial image, and each of the unmatching pairs comprises an unmatching labelled voice sample and labelled facial image;

calculating, for each of the labelled voice samples, the plurality of voice metaproperties from the labelled voice sample;

calculating, for each of the labelled facial images, the plurality of image metaproperties from the labelled facial image; and

using the plurality of voice metaproperties and the plurality of image metaproperties of the plurality of matching pairs and the plurality of unmatching pairs, and the associated labels, to train the classifier.

2. The method of claim **1**, wherein the classifier is a binary classifier.

3. The method of claim **1**, wherein calculating one voice metaproperty of the plurality of voice metaproperties comprises:

encoding the voice sample into a voice representation using a voice encoder; and

calculating the one voice metaproperty of the plurality of voice metaproperties from the voice representation;

and wherein calculating one image metaproperty of the plurality of image metaproperties comprises:

encoding the facial image into an image representation using a face encoder; and

calculating one image metaproperty of the plurality of image metaproperties from the image representation.

4. The method of claim **1**, wherein each of the metaproperties comprises an identity characteristic of an individual.

5. The method of claim **1**, wherein the metaproperties comprise at least one property selected from: age, gender, weight, body mass index (BMI), skin tone, mother tongue and accent.

6. The method of claim **1**, comprising:

obtaining a plurality of facial images;

determining a level of match between the voice sample and each the facial images;

selecting the facial images with a highest level of match; and

reconstructing the face of the speaker in the voice sample by fusing the selected facial images.

7. A system for matching a voice sample to a facial image, the system comprising:

a memory; and

a processor configured to:

obtain a voice sample and a facial image;

calculate a plurality of voice metaproperties from the voice sample;

calculate a plurality of image metaproperties from the facial image, wherein each of the image metaproperties corresponds to one of the voice metaproperties, wherein each of the voice metaproperties and the image metaproperties comprises a probability distribution providing the probabilities that the voice metaproperty or the image metaproperty equals certain values of the metaproperty; and

determine a level of match between the voice sample and the facial image, based on the plurality of voice metaproperties and the plurality of image metaproperties, by:

calculating a distance between each of the voice metaproperties and the corresponding image metaproperty;

calculating a weighted sum of the distances; and

determining that the voice sample matches the facial image if the weighted sum satisfies a threshold condition, and that the voice sample does not match the facial image otherwise,

wherein the processor is configured to calculate weights for the weighted sum operation by training a classifier and deriving the weights from the parameters of the classifier, and

wherein the processor is configured to train the classifier by:

obtaining a labelled dataset comprising a plurality of matching pairs labelled as matching pairs, and a plurality of unmatching pairs, labelled as unmatching pairs, wherein each of the matching pairs comprises a matching labelled voice sample and labelled facial image, and each of the unmatching pairs comprises an unmatching labelled voice sample and labelled facial image;

calculating, for each of the labelled voice samples, the plurality of voice metaproperties from the labelled voice sample;

calculating, for each of the labelled facial images, the plurality of image metaproperties from the labelled facial image; and

using the plurality of voice metaproperties and the plurality of image metaproperties of the plurality of matching pairs and the plurality of unmatching pairs, and the associated labels, to train the classifier.

8. The system of claim **7**, wherein the classifier is a binary classifier.

9. The system of claim **7**, wherein the processor is configured to calculate one voice metaproperty of the plurality of voice metaproperties by:

encoding the voice sample into a voice representation using a voice encoder; and

calculating the one voice metaproperty of the plurality of voice metaproperties from the voice representation;

and wherein calculating one image metaproperty of the plurality of image metaproperties comprises:

encoding the facial image into an image representation using a face encoder; and

calculating one image metaproperty of the plurality of image metaproperties from the image representation.

10. The system of claim **7**, wherein each of the metaproperties comprises an identity characteristic of an individual.

11. The system of claim **7**, wherein the metaproperties comprise at least one property selected from: age, gender, weight, body mass index (BMI), skin tone, mother tongue and accent.

12. The system of claim **7**, wherein the processor is configured to:

obtain a plurality of facial images;

determine a level of match between the voice sample and each the facial images;

selecting the facial images with a highest level of match; and

reconstruct the face of the speaker in the voice sample by fusing the selected facial images.

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