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(54) **SPLATTING-BASED DIGITAL IMAGE SYNTHESIS**

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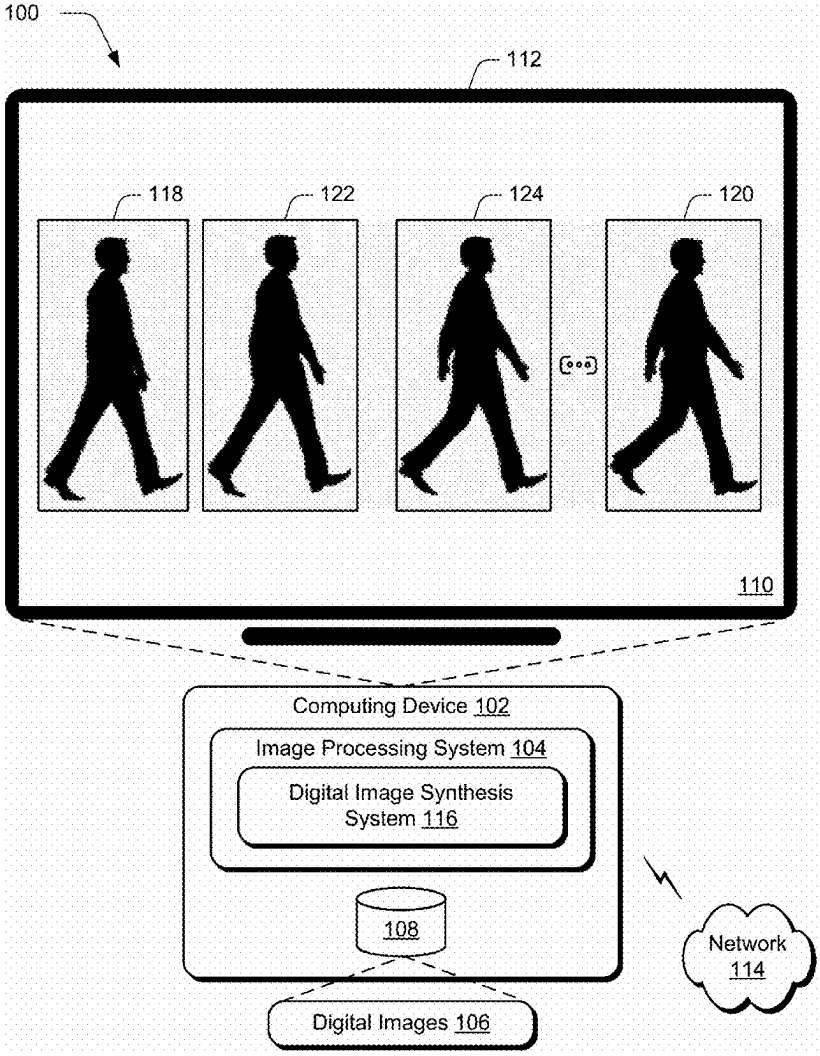
(57) **ABSTRACT**

Digital image synthesis techniques are described that leverage splatting, i.e., forward warping. In one example, a first digital image and a first optical flow are received by a digital image synthesis system. A first splat metric and a first merge metric are constructed by the digital image synthesis system that defines a weighted map of respective pixels. From this, the digital image synthesis system produces a first warped optical flow and a first warp merge metric corresponding to an interpolation instant by forward warping the first optical flow based on the splat metric and the merge metric. A first warped digital image corresponding to the interpolation instant is formed by the digital image synthesis system by backward warping the first digital image based on the first warped optical flow.



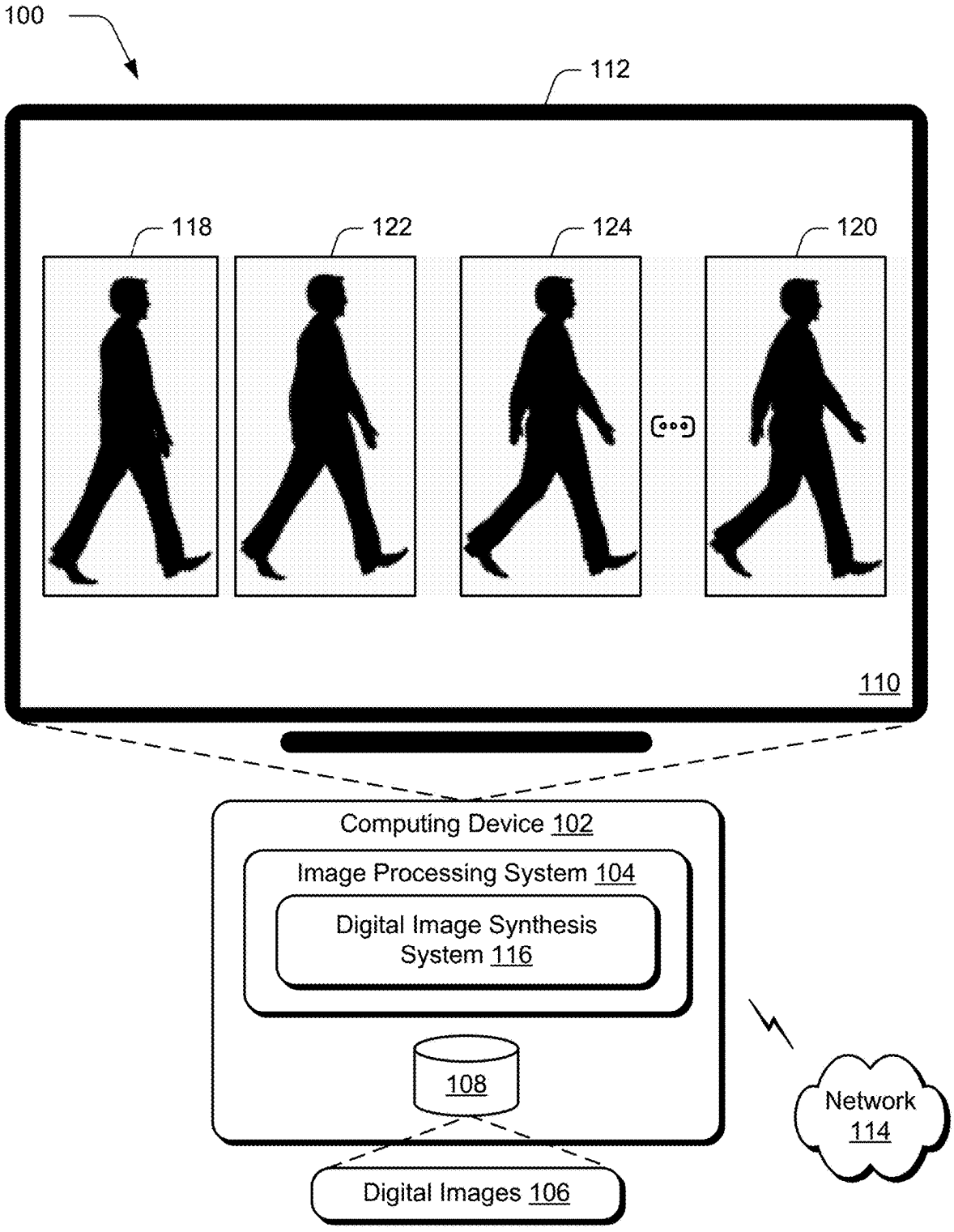

100
112
118
122
124
120
110
Computing Device 102
Image Processing System 104
Digital Image Synthesis System 116
108
Network 114
Digital Images 106

Fig. 1

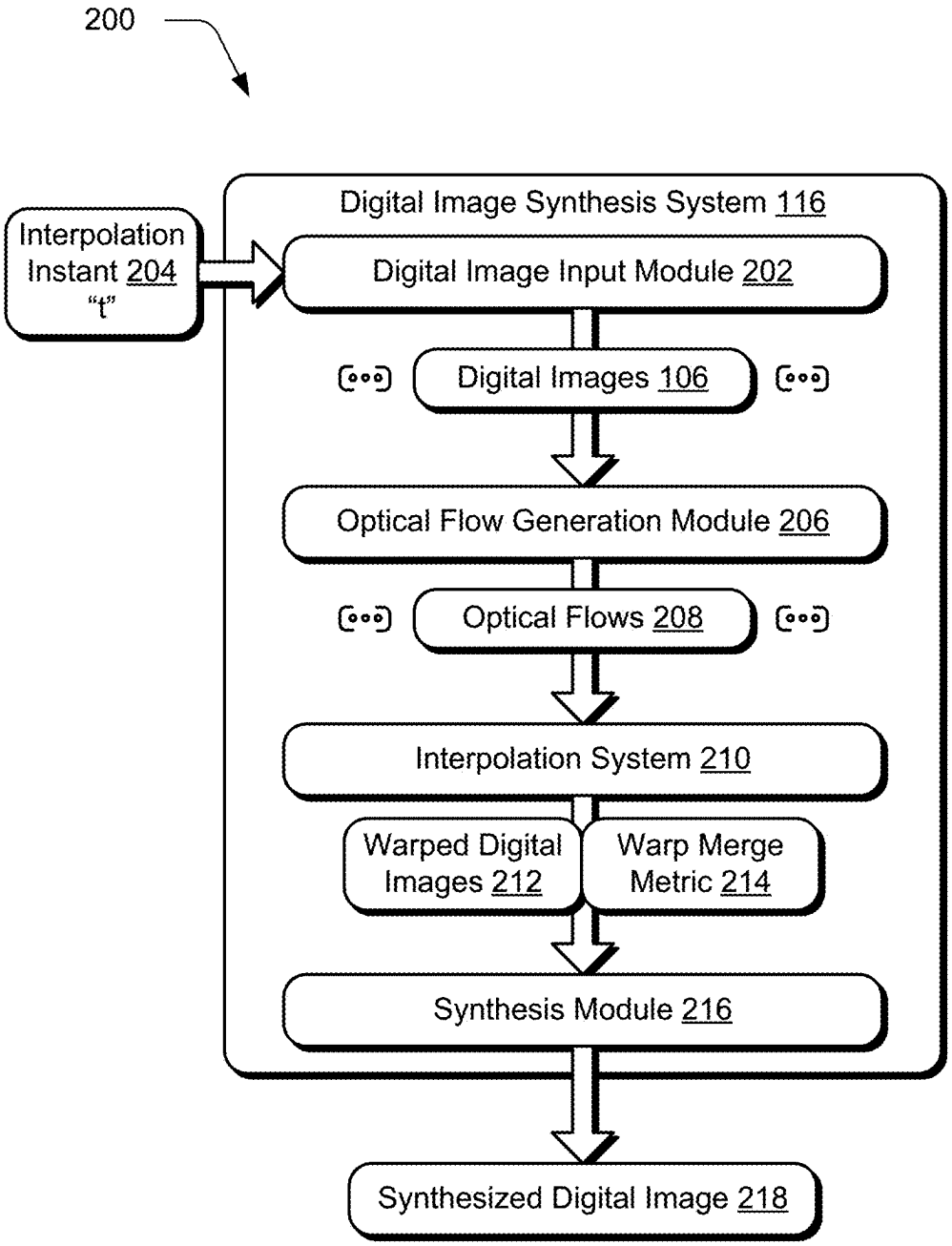

200
Digital Image Synthesis System 116
Interpolation Instant 204 "t"
Digital Image Input Module 202
Digital Images 106
Optical Flow Generation Module 206
Optical Flows 208
Interpolation System 210
Warped Digital Images 212
Warp Merge Metric 214
Synthesis Module 216
Synthesized Digital Image 218

Fig. 2

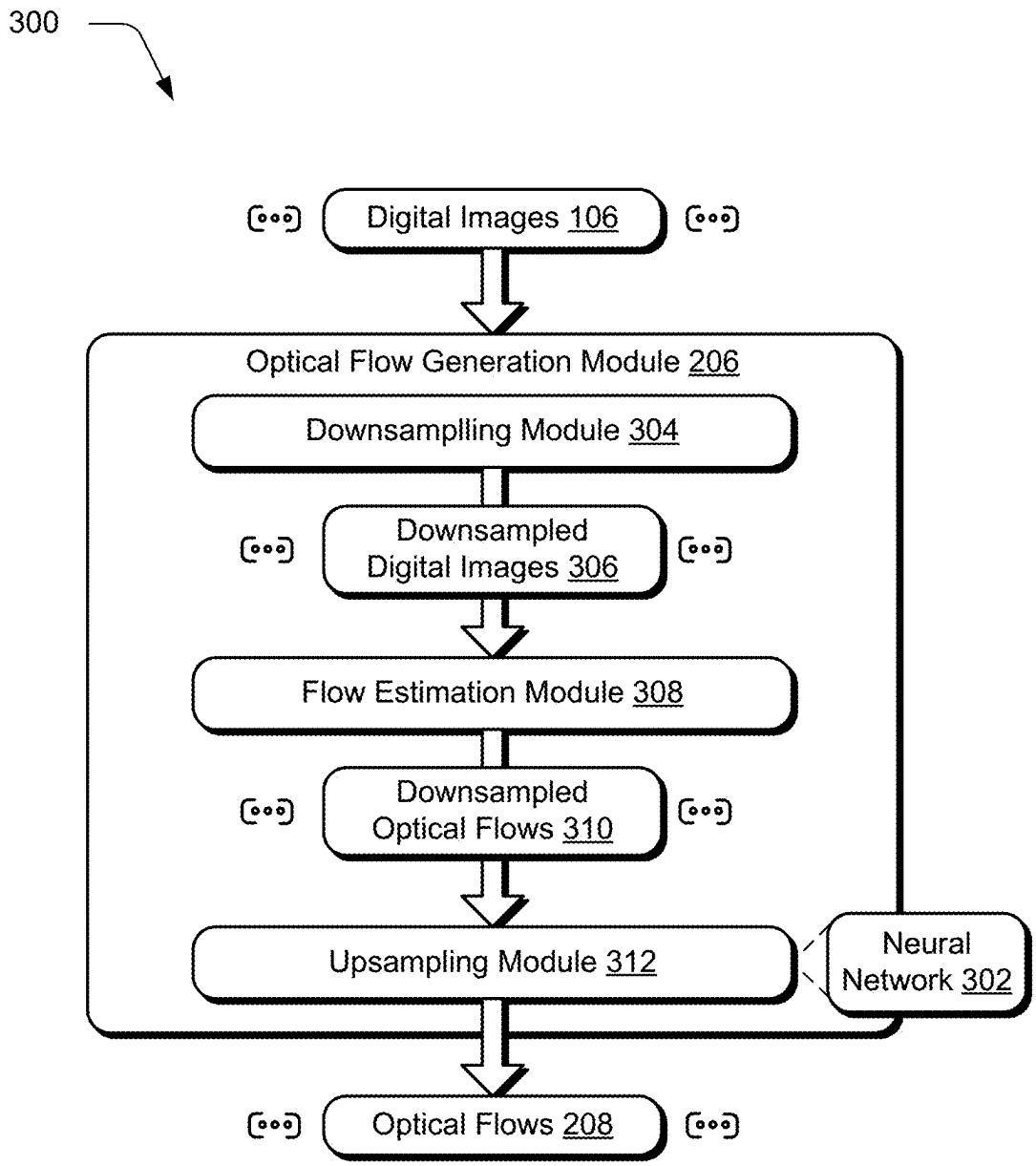

300
Digital Images 106
Optical Flow Generation Module 206
Downsamplling Module 304
Downsampled Digital Images 306
Flow Estimation Module 308
Downsampled Optical Flows 310
Upsampling Module 312
Neural Network 302
Optical Flows 208

Fig. 3

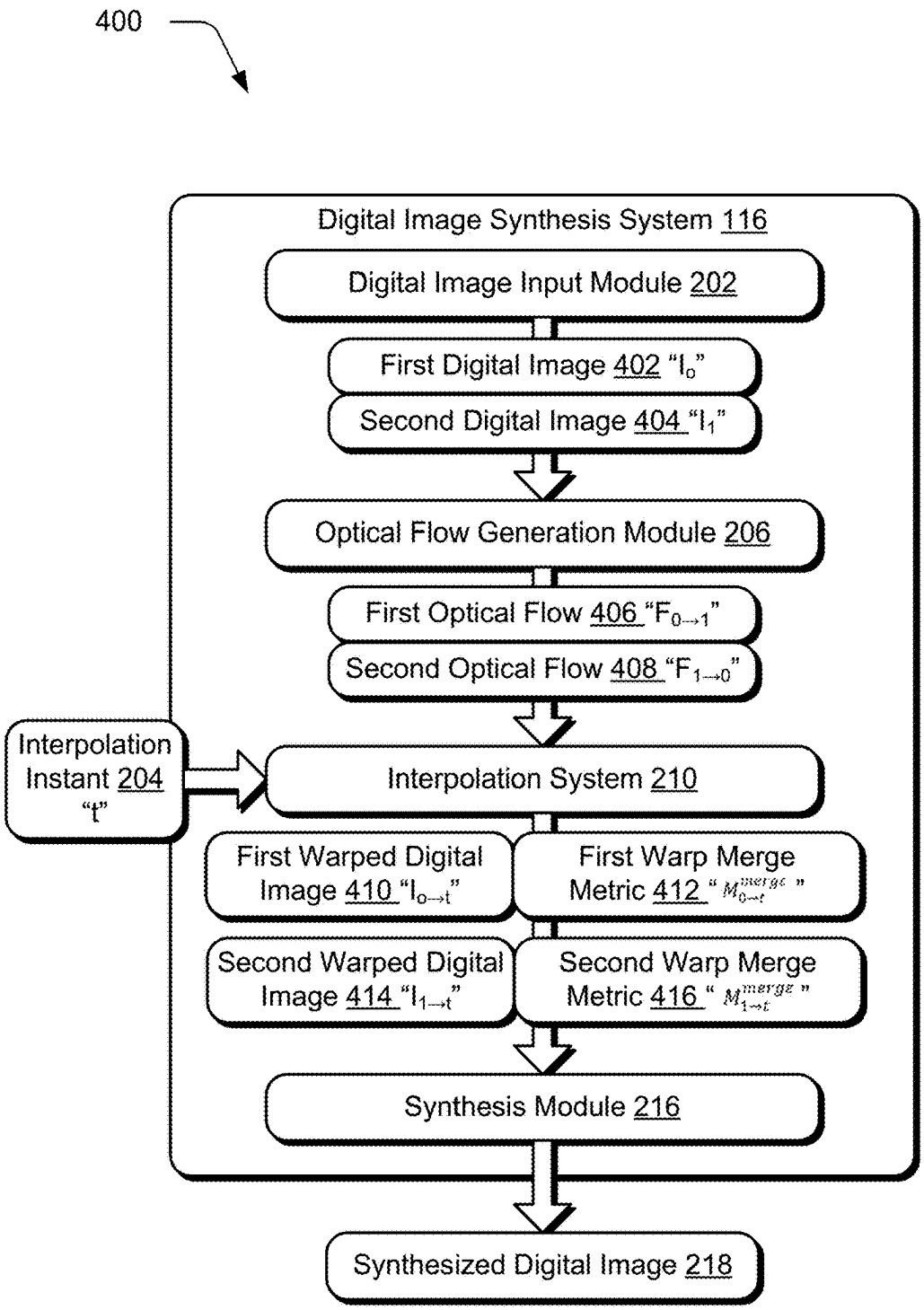

400
Digital Image Synthesis System 116
Digital Image Input Module 202
First Digital Image 402 "I_0"
Second Digital Image 404 "I_1"
Optical Flow Generation Module 206
First Optical Flow 406 "$F_{0\to1}$"
Second Optical Flow 408 "$F_{1\to0}$"
Interpolation Instant 204 "t"
Interpolation System 210
First Warped Digital Image 410 "$I_{0\to t}$"
First Warp Merge Metric 412 "$M_{0\to t}^{merge}$"
Second Warped Digital Image 414 "$I_{1\to t}$"
Second Warp Merge Metric 416 "$M_{1\to t}^{merge}$"
Synthesis Module 216
Synthesized Digital Image 218

Fig. 4

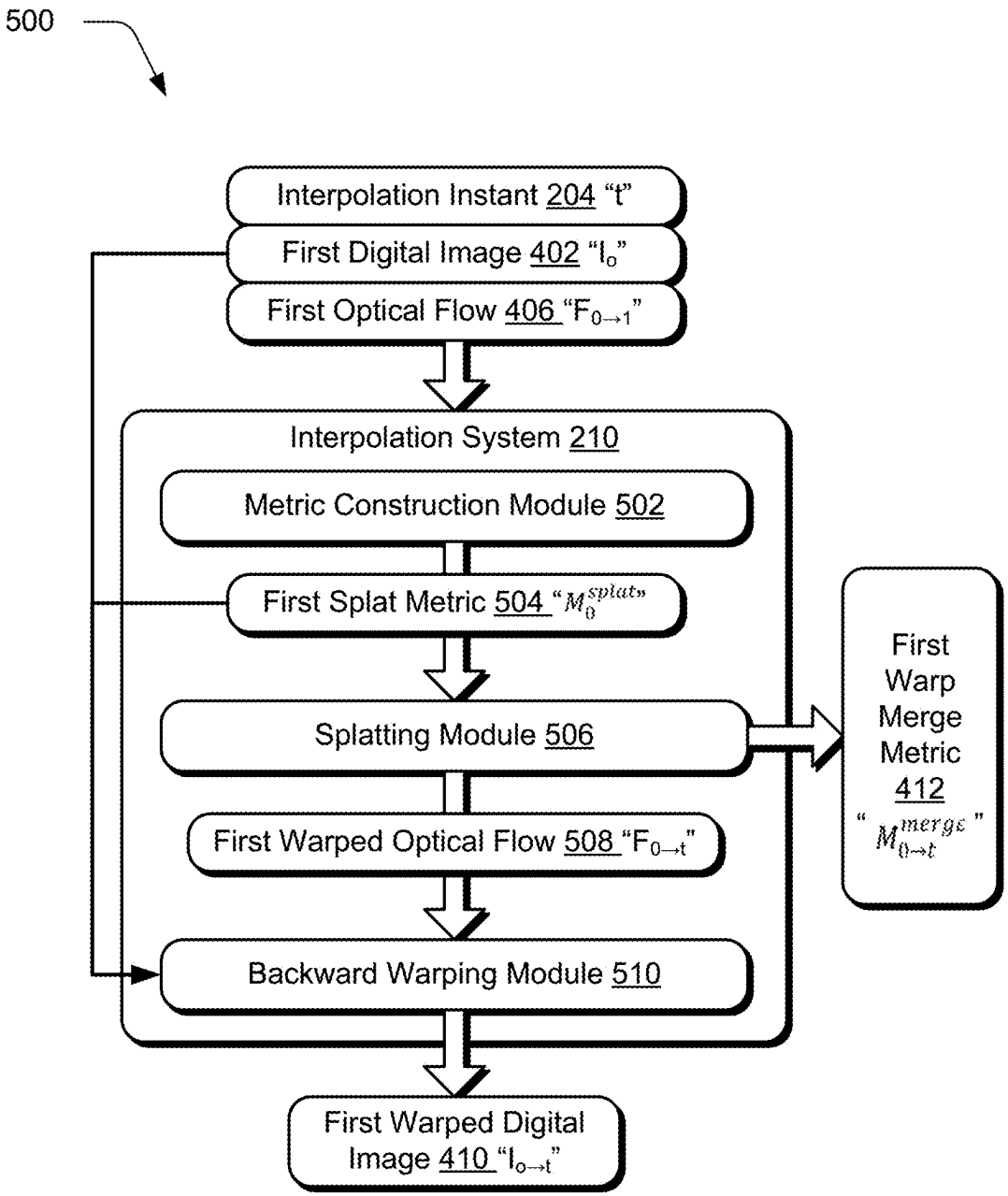

500
Interpolation Instant 204 "t"
First Digital Image 402 "I_o"
First Optical Flow 406 "$F_{0\to1}$"
Interpolation System 210
Metric Construction Module 502
First Splat Metric 504 "M_0^{splat}"
Splatting Module 506
First Warped Optical Flow 508 "$F_{0\to t}$"
Backward Warping Module 510
First Warped Digital Image 410 "$I_{o\to t}$"
First Warp Merge Metric 412 "$M_{0\to t}^{merge}$"

Fig. 5

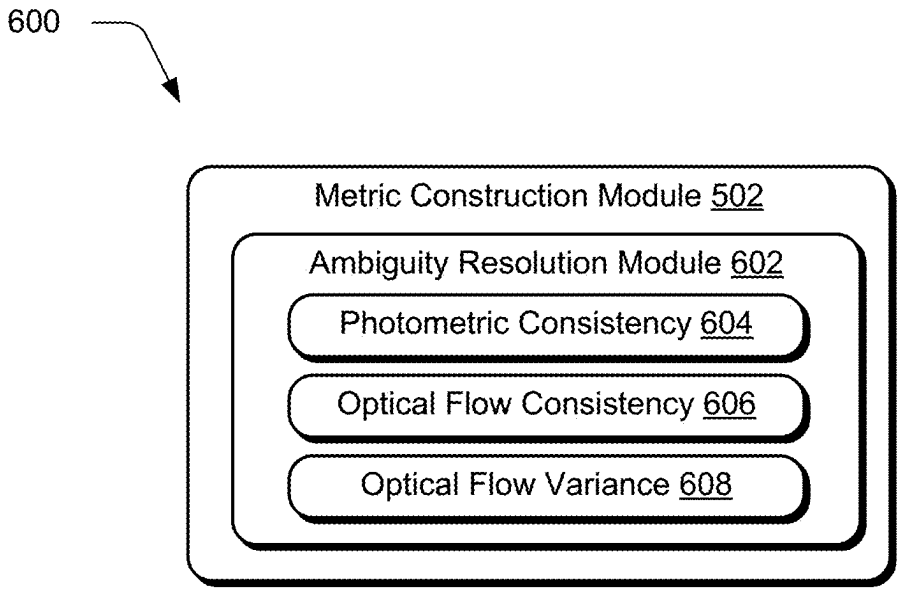

600
Metric Construction Module 502
Ambiguity Resolution Module 602
Photometric Consistency 604
Optical Flow Consistency 606
Optical Flow Variance 608

Fig. 6

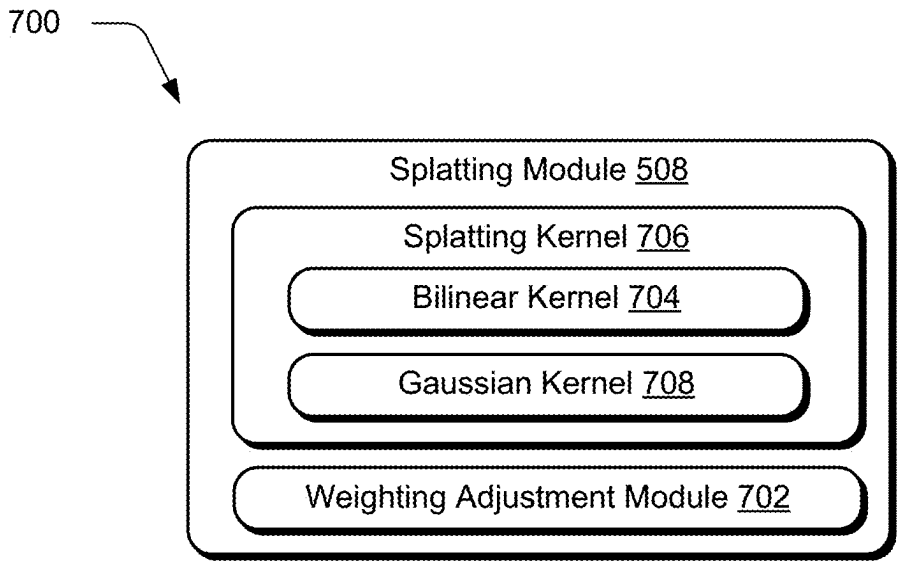

700
Splatting Module 508
Splatting Kernel 706
Bilinear Kernel 704
Gaussian Kernel 708
Weighting Adjustment Module 702

Fig. 7

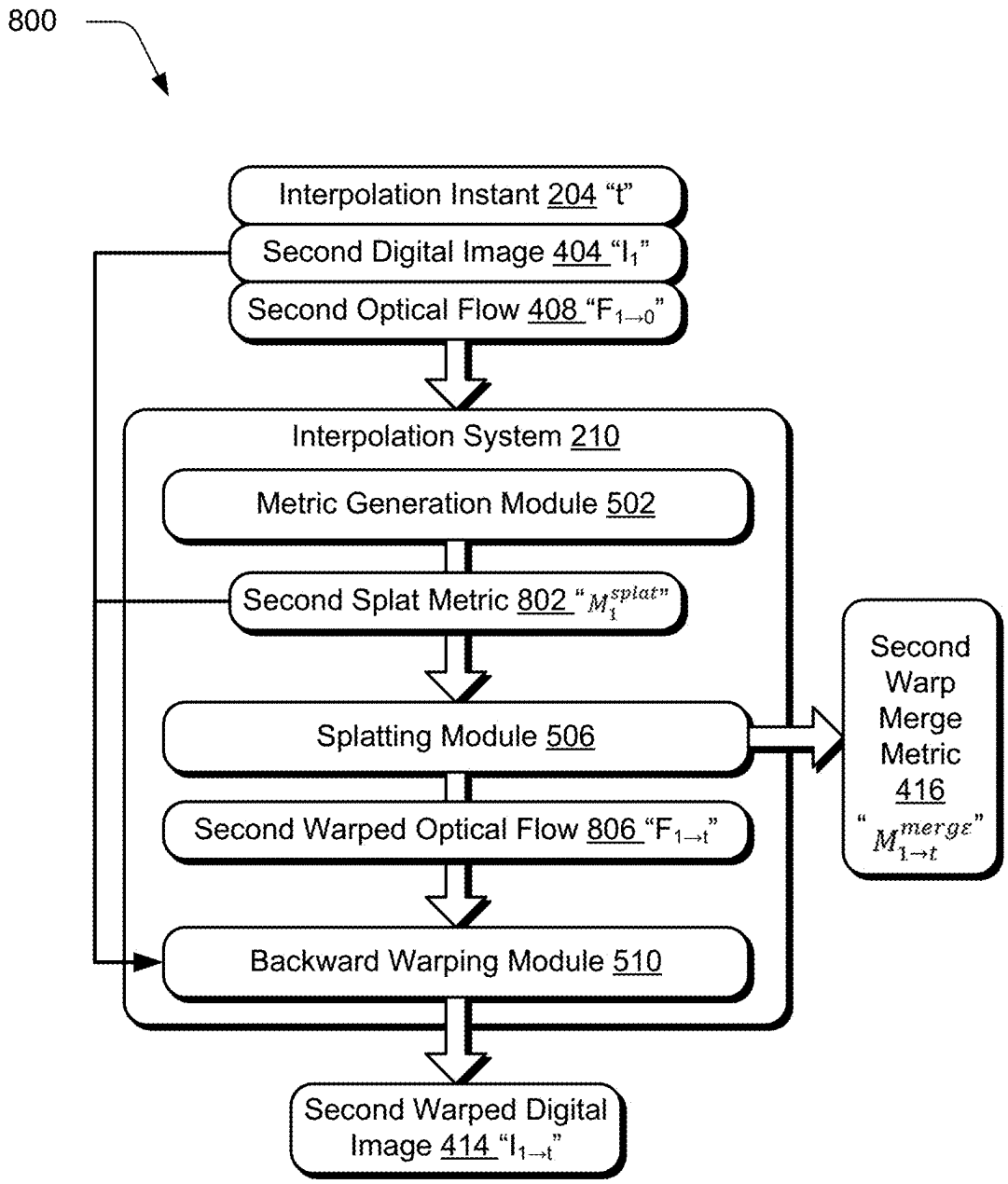

800
Interpolation Instant 204 "t"
Second Digital Image 404 "I_1"
Second Optical Flow 408 "$F_{1\to0}$"
Interpolation System 210
Metric Generation Module 502
Second Splat Metric 802 "M_1^{splat}"
Splatting Module 506
Second Warped Optical Flow 806 "$F_{1\to t}$"
Backward Warping Module 510
Second Warped Digital Image 414 "$I_{1\to t}$"
Second Warp Merge Metric 416 "$M_{1\to t}^{merge}$"

Fig. 8

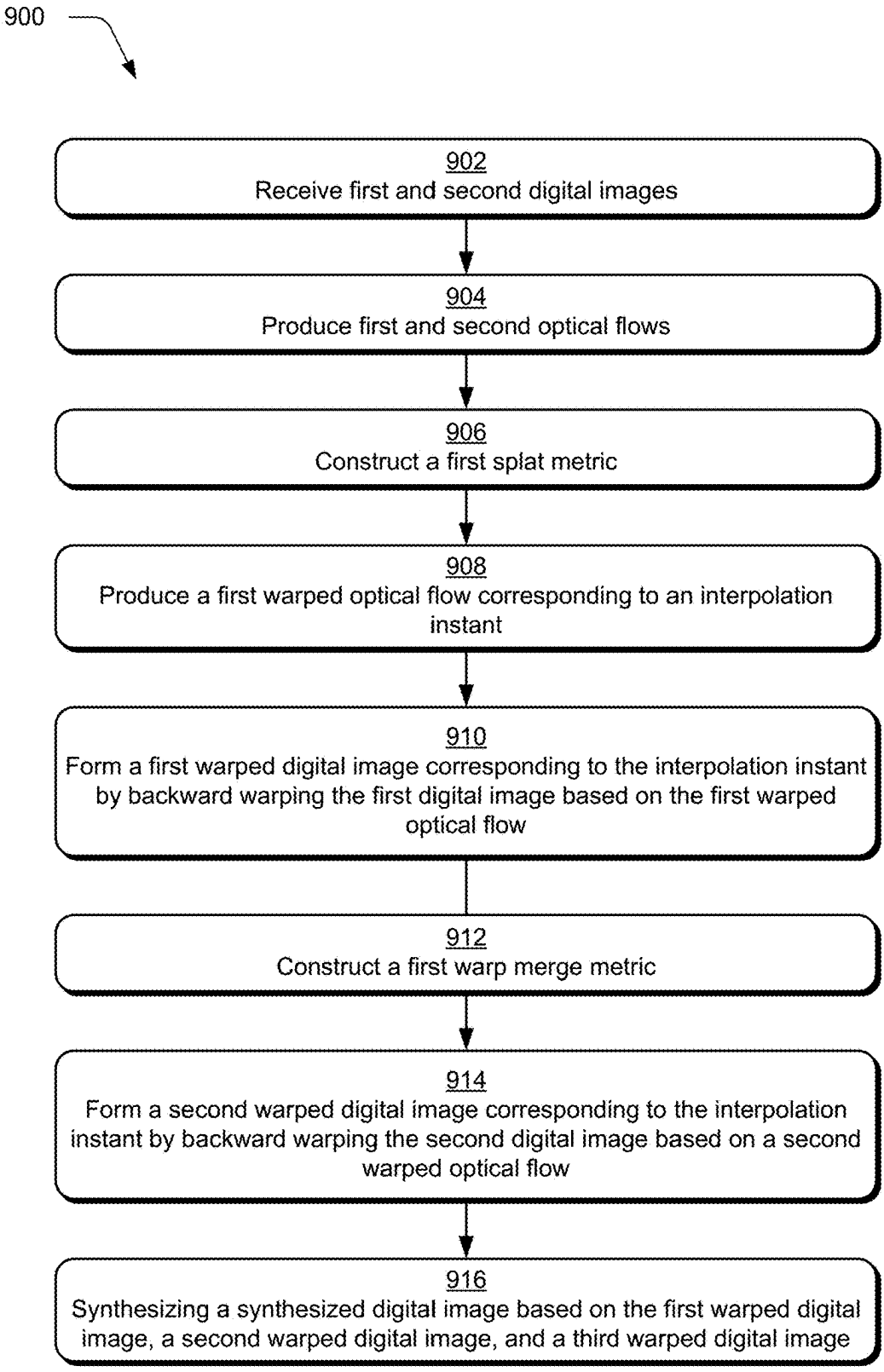

900
902
Receive first and second digital images
904
Produce first and second optical flows
906
Construct a first splat metric
908
Produce a first warped optical flow corresponding to an interpolation instant
910
Form a first warped digital image corresponding to the interpolation instant by backward warping the first digital image based on the first warped optical flow
912
Construct a first warp merge metric
914
Form a second warped digital image corresponding to the interpolation instant by backward warping the second digital image based on a second warped optical flow
916
Synthesizing a synthesized digital image based on the first warped digital image, a second warped digital image, and a third warped digital image

Fig. 9

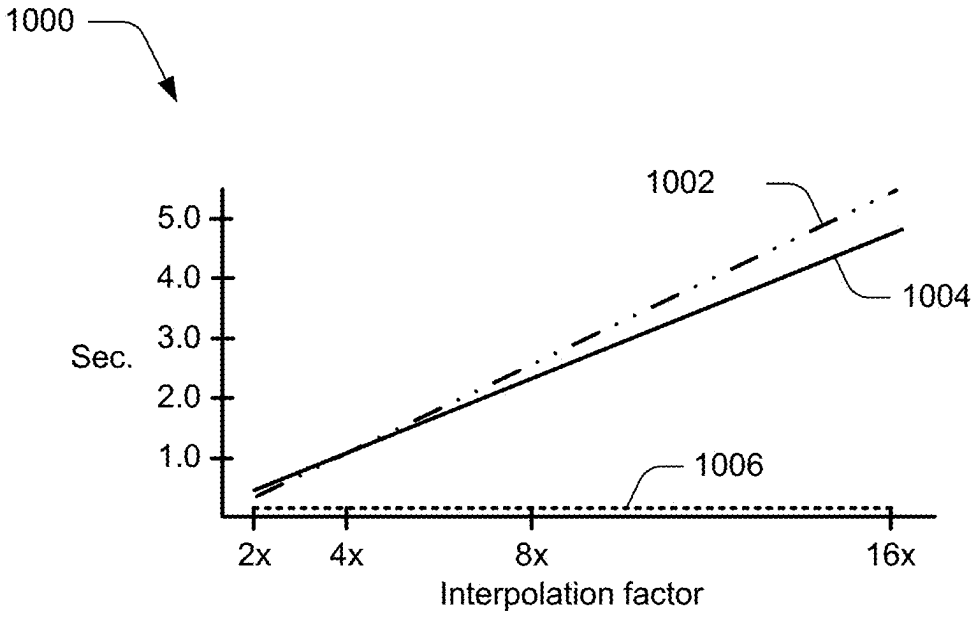
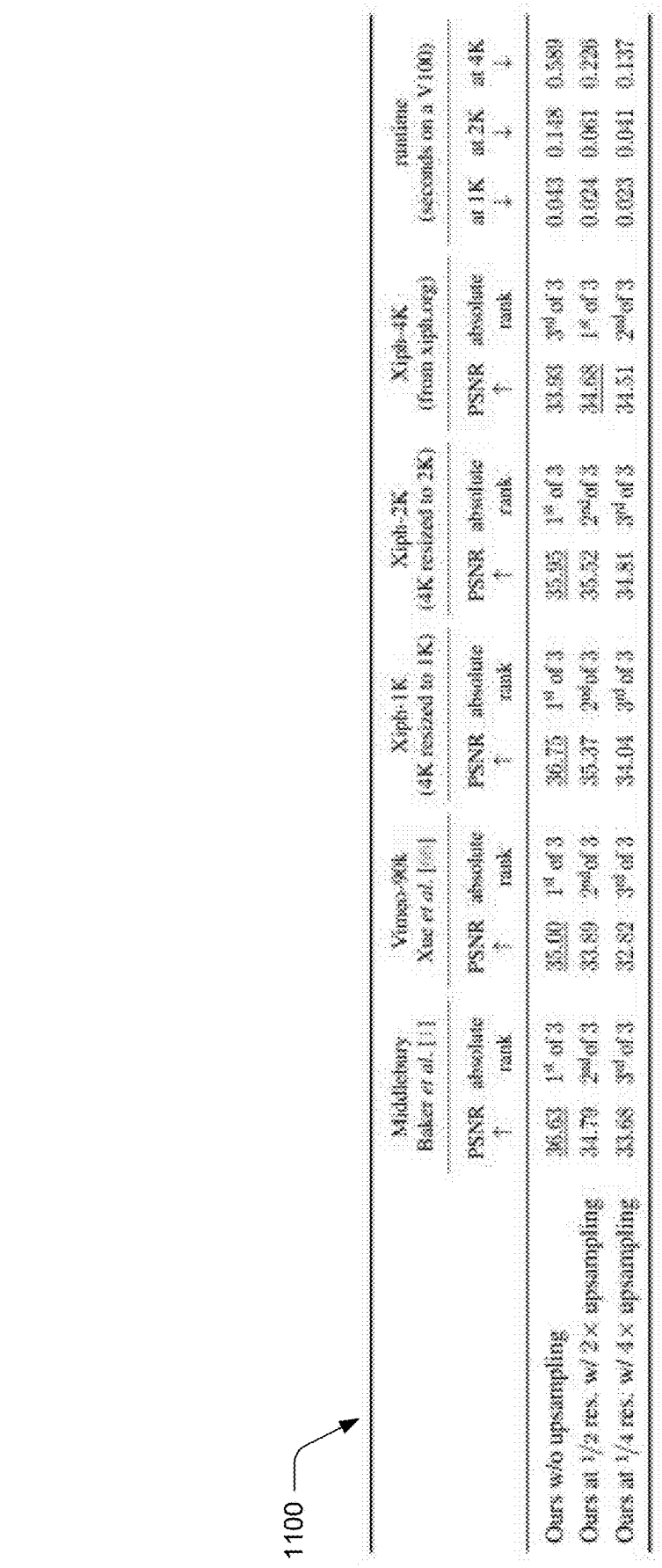

1000
1002
1004
1006
5.0
4.0
3.0
2.0
1.0
Sec.
2x
4x
8x
16x
Interpolation factor

Fig. 10



	Middlebury Baker *et al.* [11]		Vimeo-90K Xue *et al.* [100]		Xiph-1K (4K resized to 1K)		Xiph-2K (4K resized to 2K)		Xiph-4K (from xiph.org)		runtime (seconds on a V100)		
	PSNR ↑	absolute rank	PSNR ↑	absolute rank	PSNR ↑	absolute rank	PSNR ↑	absolute rank	PSNR ↑	absolute rank	at 1K ↓	at 2K ↓	at 4K ↓
Ours w/o upsampling	36.63	1st of 3	35.00	1st of 3	36.73	1st of 3	35.05	1st of 3	33.98	3rd of 3	0.043	0.148	0.589
Ours at 1/2 res. w/ 2× upsampling	34.79	2nd of 3	33.60	2nd of 3	35.07	2nd of 3	35.32	2nd of 3	34.08	1st of 3	0.024	0.061	0.220
Ours at 1/4 res. w/ 4× upsampling	33.68	3rd of 3	32.82	3rd of 3	34.04	3rd of 3	34.81	3rd of 3	34.31	2nd of 3	0.023	0.041	0.137

Fig. 11

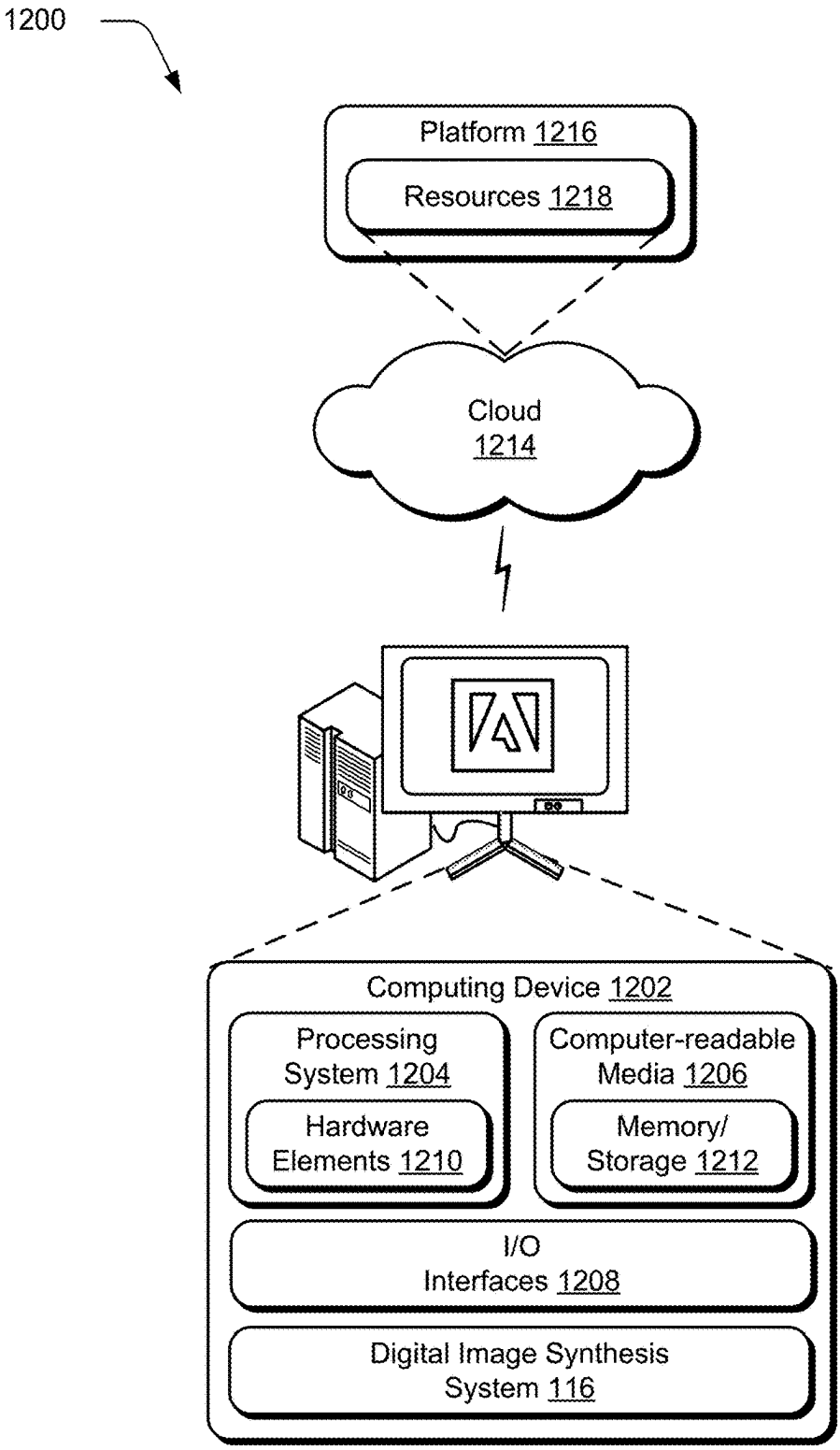

1200
Platform 1216
Resources 1218
Cloud
1214
Computing Device 1202
Processing
System 1204
Hardware
Elements 1210
Computer-readable
Media 1206
Memory/
Storage 1212
I/O
Interfaces 1208
Digital Image Synthesis
System 116

Fig. 12

SPLATTING-BASED DIGITAL IMAGE SYNTHESIS

BACKGROUND

[0001] Digital image synthesis techniques are employed by computing devices to synthesize a digital image from another digital image. These techniques are used in a variety of scenarios, examples of which include animation "inbetweening," video compression, video editing, motion blur synthesis, and so forth. Another common example involves synthesizing the digital image as a frame disposed "between" two other frames in a sequence, e.g., to form a digital video or animation having a plurality of frames.

[0002] Early conventional techniques to do so involve use of block motion estimation and compensation using performance constraints, which provide inconsistent results. Graphics accelerators were then developed to provide sufficient computational resources in support of dense motion estimation and compensation. As such, this typically involves heavy use of neural networks and a corresponding heavy use of computational resources used to implement these techniques. For example, conventional frame interpolation approaches that employ deep learning involve fully executing an entirety of a neural network for each output frame in order to resolve visual artifacts in the synthesized digital images. As such, these techniques become unwieldly in instances involving multiple frames, frames that have a high resolution, and so forth. Accordingly, execution of conventional techniques by computing devices becomes untenable in common usage scenarios due to this resource consumption.

SUMMARY

[0003] Digital image synthesis techniques are described that leverage splatting, i.e., forward warping. In one example, a first digital image and a first optical flow are received by a digital image synthesis system. The first optical flow describes pixel movement of the first digital image to a second digital image. A splat metric is constructed by the digital image synthesis system that defines a weighted map of respective pixels of the first digital image based on a parameter, e.g., photometric consistency, optical flow consistency, optical flow variance, depth maps, and so on.

[0004] From this, the digital image synthesis system produces a first warped optical flow and a first warp merge metric corresponding to an interpolation instant by forward warping the first optical flow based on the splat metric and the merge metric. A first warped digital image corresponding to the interpolation instant is formed by the digital image synthesis system by backward warping the first digital image based on the first warped optical flow. The first warp merge metric is constructed by the digital image synthesis system that defines a weighted map of respective pixels of the first warped digital image, e.g., based on the parameter.

[0005] The digital image synthesis system then synthesizes a synthesized digital image by combining the first warped digital image with a second warped digital image. This is performed based on the first warp merge metric and a second warp merge metric that defines accuracy of respective pixels within the first and second images.

[0006] A variety of other improvements are also described. Examples of these improvements include use of downsampling to increase computational resource consumption efficiency as well as accuracy in generating optical flows, use of Gaussian kernels to generate warped optical flows for respective interpolation instants, an ability to use three or more frames to synthesize a digital image, weight adjustment techniques based on a maximum pixel values at respective locations to address conventional situations involving numerical instability, and so forth.

[0007] This Summary introduces a selection of concepts in a simplified form that are further described below in the Detailed Description. As such, this Summary is not intended to identify essential features of the claimed subject matter, nor is it intended to be used as an aid in determining the scope of the claimed subject matter.

BRIEF DESCRIPTION OF THE DRA WINGS

[0008] The detailed description is described with reference to the accompanying figures. Entities represented in the figures are indicative of one or more entities and thus reference is made interchangeably to single or plural forms of the entities in the discussion.

[0009] FIG. **1** is an illustration of an environment in an example implementation that is operable to employ splatting-based digital image synthesis techniques described herein.

[0010] FIG. **2** depicts a system in an example implementation showing operation of a digital image synthesis system of FIG. **1** in greater detail.

[0011] FIG. **3** depicts an example of operation of an optical flow generation module of FIG. **2** in greater detail as employing downsampling and upsampling techniques.

[0012] FIG. **4** depicts a system in an example implementation showing operation of an interpolation system of FIG. **2** in greater detail.

[0013] FIG. **5** depicts a system in an example implementation showing operation of the interpolation system of FIG. **4** in greater detail as generating a first warped digital image and a first warp merge metric.

[0014] FIG. **6** depicts an example implementation showing operation of a metric construction module of FIG. **5** in greater detail as employing parameters usable to generate metrics to resolve ambiguities in image synthesis.

[0015] FIG. **7** depicts an example implementation showing operation of the spatting module of FIG. **5** in greater detail as employing a Gaussian kernel and a weighting adjustment module.

[0016] FIG. **8** depicts an example implementation of operation of the interpolation system of FIG. **5** to form a second warped digital image and a second warp merge metric.

[0017] FIG. **9** is a flow diagram depicting a procedure in an example implementation of automated splatting-based digital image synthesis.

[0018] FIG. **10** depicts a chart illustrating improvements in computing device operation realized through use of the spatting-based digital image synthesis techniques described herein.

[0019] FIG. **11** depicts a table illustrating improvements in computing device operation realized through use of the spatting-based digital image synthesis techniques described herein.

[0020] FIG. **12** illustrates an example system including various components of an example device that can be implemented as any type of computing device as described

and/or utilize with reference to FIGS. **1-11** to implement embodiments of the techniques described herein.

DETAILED DESCRIPTION

Overview

[0021] Conventional digital image synthesis techniques are computationally-resource intensive. This is because conventional usage scenarios employ neural networks that are executed in their entirety in order to generate each instance of a digital image in order to resolve visual artifacts. Consequently, these conventional techniques consume significant amounts of computational resources and are ill suited for repeated implementation using typical computing devices.

[0022] As shown in an example chart **1000** of FIG. **10**, for instance, execution of a first conventional technique **1002** to interpolate a given digital image by a factor of eight instead of a factor of two involves eight times the computational resources. The same is observable in a second conventional technique **1004** that involves estimating optical flow between input frames and then warping feature pyramids to a desired interpolation instant before employing a neural network to yield a final result. This is because this second conventional technique **1004** also involves repeated execution of an entirety of a neural network for each frame, again involving a corresponding increase in computational resource consumption.

[0023] Accordingly, digital image synthesis techniques are described that leverage splatting, i.e., forward warping. In these techniques, synthesis of the digital image involves a few milliseconds each time as shown at the current splatting technique **1006**. In the techniques described herein, for example, spatting of an optical flow is followed by backwards warping to generate frames without involving repeated use of an entirety of a neural network to refine the frames as involved in conventional techniques. This is achievable due to the increased visual accuracy of the described digital image synthesis techniques. Accordingly, interpolation of a given digital video by a factor of eight instead of by a factor of two involves minimal additional use of computation resources. This results in a corresponding improvement in operation of underlying computing devices that implement these techniques.

[0024] A variety of other improvements are also described in the following sections. Examples of these improvements include use of downsampling to increase computational resource consumption efficiency as well as accuracy in generating optical flows, use of Gaussian kernels to generate warped optical flows for respective interpolation instants, an ability to use three or more frames to synthesize a digital image, weight adjustment techniques based on a maximum pixel values at respective location to address conventional situations involving numerical instability, and so forth.

[0025] In one example, the digital synthesis techniques are used to synthesize a digital image at an interpolation instant between a first digital image and a second digital image. A digital image synthesis system, for instance, receives the digital images as well as an input identifying an interpolation instant "t" defining a point in time in the movement of pixels between the first and second digital images, e.g., at a point in time halfway between the movement between the frames.

[0026] An optical flow generation module is then employed to generate optical flows. A first optical flow is generated that describes movement of pixels from the first digital image to the second digital image. A second optical flow is also generated that describes movement of pixels from the second digital image to the first digital image. Thus, the interpolation instant is a point in time with respect to movements.

[0027] The digital images and optical flows are then received as an input by an interpolation system. The interpolation system is configured to generate warped digital images, which are then combined by a synthesis module to generate a synthesized digital image. To do so, warp merge metrics are generated by the interpolation system for the first and second digital images, respectively. The warp merge metrics define respective importance of individual pixels of the warped digital images. As such, these metrics are usable to combine the warped digital images in an efficient manner without reliance on subsequent refinement using a neural network as is involved in conventional techniques.

[0028] In order to generate the warped digital images and warp merge metric for the first digital image, the interpolation system receives an input identifying the interpolation instant "t" with respect to the optical flows, the first digital image, and the first optical flow. A metric construction module is employed to generate a splat metric. The splat metric is formed based on parameters that quantify an expected accuracy (e.g., confidence) of respective pixels in the first digital image and the first optical flow, respectively. Examples of these parameter include photometric consistency, optical flow consistency, optical flow variance, depth values, and so forth. This results in a splat metric configured as a weighted map defining relative importance of respective pixels of the digital image. The splat metric is usable to resolve ambiguities encountered when multiple pixels are mapped to a same location at the interpolation instant "t."

[0029] A splatting module is then employed by the interpolation system that accepts as an input the first optical flow, the first splat metric, and the first merge metric. The splatting module is configured to forward warp the first optical flow based on the metrics to form a first warped optical flow that corresponds to the interpolation instant "t," i.e., a relative point in time in movement between frames.

[0030] The first warped optical flow is then used along with the first digital image to generate a first warped digital image using backward warping that corresponds to the interpolation instant "t." A first warped metric is also generated by the spatting module as part of generating the first warped digital image. As previously described, this first warped metric describes relative importance of pixels in the first warped digital image as a weighted map, which is performable using one or more parameters described above.

[0031] In conventional splatting techniques, visual artifacts (e.g., holes) are often encountered due to divergent flow fields in the optical flow, occlusions, and so forth. Accordingly, in one example the interpolation system employs a Gaussian kernel (e.g., a 4×4 Gaussian kernel) instead of a default bilinear splatting kernel (e.g., typically defined as 2×2) for splatting the optical flows. Use of a wider kernel typically leads to blurry results when spatting colors. However, use of the Gaussian kernel to splat the optical flows (followed by backward warping) avoids these potential inaccuracies and visual artifacts and as such overcomes challenges in conventional techniques and improves opera-

tion of underlying computing devices. Similar techniques are also usable following the techniques described above to generate a second warped digital image and a second warp merge metric based on the second digital image and second optical flow. As previously described, this is also performable for additional digital images (e.g., for a third digital image and third optical flow to generate a third warped digital image and third warp merge metric, etc.) to further improve accuracy by leveraging respective merge metrics.

[0032] A synthesis module is then employed to generate a synthesized digital image by combining the warped digital images based on respective warp merge metrics. The warp merge metrics define relative importance of pixels of the warped digital image, which is based on a calculated degree of accuracy and/or confidence in the pixels. This is used to suppress influence of unreliable pixels when generating the synthesized digital image, e.g., to address movement at borders of an object. In this way, the splatting and backward warping techniques support accuracy in generation of the warped digital images and a subsequent synthesized digital image. This is performable without use of conventional refinement techniques typically implemented using neural networks. Further discussion of these and other examples and advantages are included in the following sections and shown using corresponding figures.

[0033] In the following discussion, an example environment is described that employs the techniques described herein. Example procedures are also described that are performable in the example environment as well as other environments. Consequently, performance of the example procedures is not limited to the example environment and the example environment is not limited to performance of the example procedures.

Example Digital Image Synthesis Environment

[0034] FIG. **1** is an illustration of a digital medium digital image synthesis environment **100** in an example implementation that is operable to employ techniques described herein. The illustrated environment **100** includes a computing device **102**, which is configurable in a variety of ways.

[0035] The computing device **102**, for instance, is configurable as a desktop computer, a laptop computer, a mobile device (e.g., assuming a handheld configuration such as a tablet or mobile phone), and so forth. Thus, the computing device **102** ranges from full resource devices with substantial memory and processor resources (e.g., personal computers, game consoles) to a low-resource device with limited memory and/or processing resources (e.g., mobile devices). Additionally, although a single computing device **102** is shown, the computing device **102** is also representative of a plurality of different devices, such as multiple servers utilized by a business to perform operations "over the cloud" as described in FIG. **12**.

[0036] The computing device **102** is illustrated as including an image processing system **104**. The image processing system **104** is implemented at least partially in hardware of the computing device **102** to process and transform a digital image **106**, which is illustrated as maintained in storage **108** of the computing device **102**. Such processing includes creation of the digital image **106**, modification of the digital image **106**, and rendering of the digital image **106** in a user interface **110** for output, e.g., by a display device **112**. Although illustrated as implemented locally at the computing device **102**, functionality of the image processing system **104** is also configurable as whole or part via functionality available via the network **114**, such as part of a web service or "in the cloud."

[0037] An example of functionality incorporated by the image processing system **104** to process the image **106** is illustrated as a digital image synthesis system **116**. The digital image synthesis system **116** is representative of functionality to synthesize a digital image **106** based on another digital image. Image synthesis techniques are employed in a wide range of usage scenarios, examples of which include animation "inbetweening," video compression, video editing, motion blur synthesis, and so forth. Another example involves automated synthesizing of the digital image as a frame disposed "between" two other frames in sequence, e.g., to form a digital video or animation having a plurality of frames.

[0038] In the illustrated implementation in the user interface **110**, for instance, a first digital image **118** and a second digital image **120** are utilized as a basis by the digital image synthesis system **116** to synthesize a plurality of digital images, examples of which include a first synthesized digital image **122** and a second synthesized digital image **124**. The first and second synthesized digital images **122**, **124** correspond to interpolation instants at respective times in motion exhibited between the first and second digital images **118**, **120**, e.g., based on one or more optical flows generated from the images.

[0039] A variety of conventional techniques have been employed to support frame interpolation, however these techniques can introduce visual artifacts, incur significant computational resource costs, and so on. Initial conventional examples are based on block-level motion estimates that include overlapping block motion compensation, adaptively handling overlapping blocks, detecting and handling occlusions, considering multiple motion estimates, and estimating a dense motion field at the interpolation instant. In another conventional example, motion compensation is based on dense estimates that includes layered warping, occlusion reasoning for temporal interpolation, warping with transition points, and using warping as a metric to evaluate optical flow.

[0040] Although splatting (also referred to as forward warping) has been used in some conventional scenarios, these scenarios involve deep learning using machine learning techniques to resolve visual artifacts caused by inaccuracies in the techniques. Thus, these conventional splatting techniques are not differentiable or capable of being parallelized, which prohibits use of ordering and selecting a candidate flow in cases where multiple source pixels map to the same target location or iteratively filling holes. In contrast, the digital image synthesis system **116** supports differentiable operations as part of digital image synthesis that are capable of being parallelized through use of optical flow splatting and backward warping. Further, these the digital image synthesis system **116** is trainable end-to-end and therefore improve accuracy of components contained therein as further described below.

[0041] Another conventional category of conventional frame interpolation approaches accepts two digital images as an input and interpolates a frame at a time between the inputs. Each of these conventional techniques, however, involve use of a neural network to infer the interpolation result at a desired instant. The conventional techniques either use a neural network to refine warped representations

of the input images or use a neural network to infer the motion from the desired interpolation instant to the input images. Use of such neural networks, however, is computationally challenging, especially at high resolutions. This is in contrast to splatting-based synthesis techniques utilized by the digital image synthesis system **116** where, given optical flow estimates between digital images **106**, synthesizes the interpolation result (i.e., a synthesized digital image) at a point in time by using relatively few primitive image operations that are computationally efficient. Further discussion of these and other advantages is included in the following sections and shown in corresponding figures.

[0042] In general, functionality, features, and concepts described in relation to the examples above and below are employed in the context of the example procedures described in this section. Further, functionality, features, and concepts described in relation to different figures and examples in this document are interchangeable among one another and are not limited to implementation in the context of a particular figure or procedure. Moreover, blocks associated with different representative procedures and corresponding figures herein are applicable together and/or combinable in different ways. Thus, individual functionality, features, and concepts described in relation to different example environments, devices, components, figures, and procedures herein are usable in any suitable combinations and are not limited to the particular combinations represented by the enumerated examples in this description.

Splatting-Based Digital Image Synthesis

[0043] The following discussion describes splatting-based digital image synthesis techniques that are implementable utilizing the previously described systems and devices. Aspects of the procedures are implemented in hardware, firmware, software, or a combination thereof. The procedures are shown as a set of blocks that specify operations performed by one or more devices and are not necessarily limited to the orders shown for performing the operations by the respective blocks. In portions of the following discussion, reference will be made to FIGS. **1-12** and in parallel to the procedure **900** of FIG. **9**.

[0044] FIG. **2** depicts a procedure **200** in an example implementation showing operation of the digital image synthesis system **116** in greater detail as automatically synthesizing a digital image. The digital image synthesis system **116** includes a digital image input module **202** that is configured to receive an input specifying digital images **106** (e.g., first and second digital images (block **902**)) that are to be used as a basis to synthesize a digital image as well as an input specifying an interpolation instant **204** "t." The interpolation instant **204** defines a relative amount of time with respect to movement between first and second digital frames, e.g., on a scale from zero to one. An interpolation instant of "0.5," for instance, defines a midway point in the movement between first and second digital images, e.g., frames.

[0045] An optical flow generation module **206** is then utilized to produce optical flows **208** based on the digital images **106**. In a two-image bidirectional example, the optical flow generation module **206** produces an optical flow from a first digital image to a second digital image. A second optical flow is also produced from the second digital image to the first digital image (block **904**). Optical flow is a pattern of apparent motion within a visual scene caused by relative motion between an observer and the scene. Techniques usable to estimate optical flow include phase correlation, block-based techniques, estimation of motion as instantaneous image velocities, differential techniques, variational techniques, discrete image displacements, discrete optimization techniques, gradient-based optical flow, and so forth.

[0046] FIG. **3** depicts an example **300** of operation of the optical flow generation module **206** in greater detail as employing downsampling and upsampling techniques that support increased computational resource efficiency and accuracy. In this example, the optical flow generation module **206** is configured to estimate flow at a lower resolution (typically corresponding to a resolution, for which, a machine-learning model is trained) which is then upsampled before use to warp frames as further described below.

[0047] Conventional techniques used to compute optical flow are typically trained for use at a predetermined resolution (e.g., 1k or 2k), and thus can fail when confronted with higher resolution inputs, e.g., 4k video. Accordingly, the optical flow generation module **206** in this example is configured to compute optical flow for high-resolution digital images at a lower resolution and then use a neural network **302** to iteratively upsample the optical flow to correspond to a resolution of the inputs, i.e., the digital images **106**. In an implementation, the upsampling is performed by a neural network that is guided by the input digital images, e.g., the first and second digital images in high (i.e., "original") resolution.

[0048] A downsampling module **304**, for instance, is configured to generate downsampled digital images **306** from the input digital images **106**. The downsampled digital images **306** have a resolution that approximates a resolution used to train the neural network **302**. The downsampled digital images **306** are then processed by a flow estimation module **308** to estimate downsampled optical flows **310**, e.g., from a first downsampled digital image to a second downsampled digital image, from the second downsampled digital image back to the first downsampled digital image, and so forth. An upsampling module **312** then employs the neural network **302** to generate the optical flows **208** by upsampling the downsampled optical flows **310** over a number of iterations.

[0049] Specifically, given a flow estimate at a resolution of "x" as well as two input digital images at a resolution of "2·x," the upsampling module **312** estimates flow at a resolution of "2·x" through a sequence of four convolutions and activations in between. To upsample a given flow estimate (i.e., downsampled optical flows **310**) by a factor of four, the upsampling module **312** is executed twice. In practice, accuracy increases have been realized by guiding the upsampling using the input digital images **106** as well as the parameters of photometric consistency, optical flow consistency, and optical flow variance as further described in relation to FIG. **6** as these parameters also encode useful properties of the optical flow. In an implementation, operation of the upsampling module **312** is configured for simplified execution without using spatially-varying upsampling kernels, normalized convolution upsampling, or self-guided upsampling to increase performance and reduce computational cost. As illustrated by an example chart **1100** of FIG. **11** depicting real world scenarios, it has also been observed that estimation of optical flow at lower resolutions and subsequent upsampling is beneficial in terms of runtime and also quality.

[0050] The optical flows **208** are then provided by the optical flow generation module **206** as an input to an interpolation system **210** to generate warped digital images **212** and warp merge metrics **214**. The warp merge metrics **214** describe "how good is that construction" for pixels in the warped digital images **212**, and as such define relative importance of the pixels. Thus, the warp merge metrics **214** define weights as a weight map of respective pixels in the warped digital images **212**, which are then used by a synthesis module **216** to generate the synthesized digital image **218** by combining the pixels based on these weights.

[0051] In this way, the digital image synthesis system **116** employs a splatting-based approach that is configured to resolve ambiguities where multiple pixels from an input digital image map to a same location, generate warped digital images **212** without introducing visual artifacts that involved machine-learning models to resolve using conventional techniques, and merge the warped digital images **212**. Further discussion of generation of the warped digital images **212** and the warp merge metrics **214** are described in greater detail in the following discussion and shown in corresponding figures.

[0052] FIG. **4** depicts a system **400** in an example implementation showing operation of the digital image synthesis system **116** of FIG. **3** in greater detail as performing digital image synthesis for first and second digital images **402**, **404**. In the following discussion, the synthesized digital image **218** is synthesized as an intermediate digital frame disposed at a point in time relative to movement between first and second digital images **402**, **404**. Accordingly, the first digital image **402** is denoted as "I_0" and the second digital image **404** as "I_1." The optical flow generation module **206** generates the first optical flow **406** "$F_{0\to1}$" describing movement of pixels from "I_0" to "I_1." Likewise, the second optical flow **408** "$F_{1\to0}$" describes movement of pixels from "I_1" to "I_0."

[0053] The interpolation instant **204** (e.g., "t") is disposed relative to that flow. The interpolation system **210** is then tasked in this example to form a first warped digital image **410** "$I_{0\to t}$," based on the first digital image **402** "I_0" and a first warp merge merge metric **412** "$M_{0\to t}{}^{merge}$" that is configured as a weighted map describing relative importance of pixels in the first warped digital image **410**. Similarity, the interpolation system **210** forms a second warped digital image **414** "$I_{1\to t}$" based on the second digital image **404** "I_1" and a second warp merge metric **416** "$M_{0\to t}{}^{merge}$" that is configured as a weighted map describing relative importance of pixels in the second warped digital image **414**. As described above, the first and second warped digital images **410**, **414** are then combined by the synthesis module **216** based on the first and second warp merge metrics **412**, **416** (and more particularly weights defined for respective pixels from the maps) to form the synthesized digital image **218**.

[0054] FIG. **5** depicts a system **500** in an example implementation showing operation of the interpolation system **210** of FIG. **4** in greater detail as generating a first warped digital image **410** and first warp merge metric **412**. The interpolation system **210** begins in this example by receiving the interpolation instant **204** "t", first digital image **402** "I_0," and first optical flow **406** "$F_{\to1}$."

[0055] A metric construction module **502** is first employed by the interpolation system **210** to construct a first splat metric **504** "$M_0{}^{splat}$" splat" (block **906**). A splatting module **506** then receives the first digital image **402** "I_0" and the first splat metric **504** "$M_0{}^{splat}$" as an input. Based on these inputs, the splatting module **506** is configured to produce a first warped optical flow **508** "$F_{0\to t}$" that describes optical flow at the interpolation instant **204** "t" using forward warping (block **908**).

[0056] A splat metric is a two-dimensional image/matrix that weights each pixel in the input (e.g., the first digital image **402**) and is also configurable as any other type of feature representation, e.g., for the merge metric as described below. The weight is used to resolve ambiguities when two or more pixels in the input map to the same target location in a forward warped/splatted output. The splat metric is configurable based on the inverse distance of a pixel to the camera such that a pixel closer to the camera has a higher weight than a pixel further away from the camera, e.g., to follow z-buffering in computer graphics. Thus, the splat metric is configured to aide resolution of self-intersections caused by movement, e.g., when multiple pixels map to a same location.

[0057] Likewise, the merge metric as further described below is a two-dimensional image/matrix that specifies weights each pixel in the input, e.g., a warped digital image, optical flow, etc. The weight is then used to combine multiple warped images/feature representations to a single output image/feature representation. The merge metric, for instance, is usable to describe reliability of an underlying optical flow vector as used to synthesize an output pixel, e.g., if the optical flow is unreliable then the result is unreliable too such as typically exhibited at motion boundaries. Thus, the merge metric supports techniques to pick/weight/combine pixels at each location when combining two or more partial results.

[0058] The merge metric, like the splat metric, is obtained at the interpolation instant "t" of the input. That is, for "I_0" the splat metric "M^{splat}" and the merge metric "M^{merge}" are obtained at "t=0." However, "M^{merge}" at "t=0.5" is used by a backward warping module to interpolate a frame at that time. As such, the interpolation system **210** is configured to splat the first digital image **402** "I_0" to "t=0.5" but also "M^{merge}" as generating a first warp merge metric **412** "$M_{0\to t}{}^{merge}$". The first splat metric **504** "$M_{0\to t}{}^{splat}$" is used to resolve ambiguities when pixels map to a same location.

[0059] FIG. **6** depicts an example implementation **600** showing operation of a metric construction module **502** of FIG. **5** in greater detail as employing parameters (e.g., measures) usable to generate metrics to resolve ambiguities. In order to generate these metrics, the metric construction module **502** employs an ambiguity resolution module **602** that is configured to employ a variety of criteria usable to resolve ambiguities and/or define "importance" of respective pixels in an input, e.g., a digital image, optical flow, or other feature representation. Illustrated examples of these parameters include photometric consistency **604**, optical flow consistency **606**, and optical flow variance **608**. Other examples are also contemplated, such as image depth.

[0060] Photometric consistency **604** is definable using backward warping "$\overleftarrow{\omega}(\bullet)$" as:

$$\psi_{photo} = \left\| I_0 - \overleftarrow{\omega}(I_1, F_{0\to1}) \right\|$$

In practice, photometric consistency accuracy is challenged when confronted by brightness changes, as is frequently the

case with changes in shading. As such, optical flow consistency **606** may also be considered, which is defined as:

$$\psi_{flow} = \left\| F_{0\to1} + \overleftarrow{\omega}(F_{1\to0}, F_{0\to1}) \right\|$$

Optical flow consistency **606** is based on consistency in mapping flow of a pixel from a target back to a source, which is invariant to brightness changes and particularly useful for determining the splat metric "M^{splat}".

[0061] Optical flow variance **608** indicates local changes in flow as:

$$\psi_{varia} = \left\| \sqrt{G(F_{0\to1}^2) - G(F_{0\to1})^2} \right\|$$

where "G(•)" denotes a "3×3" Gaussian filter. Optical flow variance **608** is high in areas with discontinuous flow, as is the case at motion boundaries. Optical flow estimates tend to be inaccurate at boundaries, which makes this measure particularly useful for the merge metric "M^{merge}".

[0062] In an implementation, the ambiguity resolution module **602** combines these measures to define the splat metric "M^{splat}" and the merge metric "M^{merge}," respectively, as:

$$M^{splat} = \frac{1}{1 + \alpha_p^s \cdot \psi_{photo}} + \frac{1}{1 + \alpha_f^s \cdot \psi_{flow}} + \frac{1}{1 + \alpha_v^s \cdot \psi_{varia}}$$

where

$$\langle \alpha_p^s, \alpha_f^s, \alpha_v^s \rangle$$

are tunable parameters. The merge metric "M^{merge}" is defined similarity as

[0063] $\langle \alpha_p^m, \alpha_f^m, \alpha_v^m \rangle$

[0064] In an implementation, these six parameters are initially set to "1" and learned through end-to-end training as part of machine learning. Other techniques are also employable, including use of a neural network to merge the individual parameters. Thus, the splat metric "M^{splat}" and the merge metric "M^{merge}" are produced using photometric consistency **604**, optical flow consistency **606**, and optical flow variance **608** in this example, but are weighted differently and thus have separate alpha values as shown above.

[0065] As described above, the interpolation system **210** is based on splatting, also referred to as forward warping. The challenge with spatting is that in some instances multiple pixels from a source map to a same location in a target, which creates an ambiguity that in a context of deep learning is resolves differentiably. Once convention technique to resolve this is referred to as "softmax splatting," see further Simon Niklaus and Feng Liu. "Softmax Splatting for Video Frame Interpolation." *In IEEE Conference on Computer Vision and Pattern Recognition,* 2020. However, in has been determined herein that this technique as conventionally implemented includes a numerical instability which causes this technique to fail on conventional computing devices due to limitations in floating point calculations.

[0066] For example, given a first digital image "I_0," a first optical flow "$F_{0\to1}$" that maps pixels in first digital image "I_0" to the target time/location defined by interpolation instant "t" and a weight map "Z_0" to resolve ambiguities, softmax splatting is defined as:

$$\vec{\sigma}(I_0, F_{0\to t}, Z_0) = \frac{\vec{\Sigma}(\exp(Z_0) \cdot I_0, F_{0\to t})}{\vec{\Sigma}(\exp(Z_0), F_{0\to t})}$$

where "$\vec{\Sigma}(\bullet)$" is summation splatting and "Z_0" is used to weight pixels in the first digital image "I_0" to resolve cases where multiple pixels map to the same target location. The weight map "Z_0" in this example supports an importance metric, e.g., as a soft inverse z-buffer.

[0067] In real world scenarios, the softmax operator is not implementable as defined above since it is numerically unstable, e.g., "exp(X)" quickly exceeds a 32-bit floating point when "X>50." Since "softmax(X+c)=softmax(X)" for any "c," "softmax(X')" is usable in stances instead where "X'=X−max(X)." However, this is not directly usable for softmax splatting. For example, consider a weight map "Z_0" with a first element set to "1000" and each other element set to "∈[0, 1]." Shifting the weights by "−1000" effectively sets each weight but one to a value of "1" and reduces the overall operation to average splatting, thus ignoring "Z_0" altogether.

[0068] To address this, the splatting module **506** employs a weighting adjustment module **702** as shown in an example implementation **700** of FIG. **7** that looks at a maximum weight at each location, instead of an entire image, and subtracts that before taking the exponent. As a result, the weights are adaptively shifted at the destination location where multiple source pixels overlap. To do so, the weight map "Z_0" is first warped to interpolation instant "t" to form "$Z_{0\to t}^{max}$" which denotes a maximum weight for each pixel in the destination location. This is computable in parallel using an atomic max. This step can be implemented without being differentiable as it is used to make softmax splatting numerically stable. A value of "$Z_{0\to t}^{max}[p]$" is subtracted from "$Z_0[q]$" before applying the exponential function when warping from a point "q" to a point "p," analogous to what is typically performed when implementing softmax.

[0069] Thus, numerically stable softmax splatting as implemented by the splatting module **506** is definable as:

$$\text{let } u = p - (q + F_{0\to t}[q])$$

$$I_t[p] = \frac{\sum_{\forall q \in I_0} b(u) \cdot \exp(Z_0[q] - Z_{0\to t}^{max}[p]) \cdot I_0[q]}{\sum_{\forall q \in I_0} b(u) \cdot \exp(Z_0[q] - Z_{0\to t}^{max}[p])}$$

$$b(u) = \max(0, 1 - |u_x|) \cdot \max(0, 1 - |u_y|).$$

where "b(•)" is a bilinear kernel **704**, which is an example of a splatting kernel **706** used by the splatting module **506**. This technique has been found in practice to result in consistent improvement in interpolation quality and hence underlying operation of computing devices that implement these techniques.

[0070] Thus, the first step in the splatting-based synthesis technique implemented by the interpolation system **210** for video frame interpolation is to warp the first digital image **402** "I_0" and the second digital image **40** "I_1" to a desired interpolation instant "t" using the first optical flow **406**

"$F_{0\to1}$" and the second optical flow **408** "$F_{1\to0}$", respectively. However, directly spatting the input digital images directly results in visual artifacts caused when multiple pixels map to the same target location. To address this ambiguity, the interpolation system **210** employs an auxiliary weight "M^{splat}" that serves as a soft inverse z-buffer as described above.

[0071] In practice, naive application of softmax splatting leads to visual artifacts and introduces blurriness. To address this, the interpolation system **210** employs warping-based interpolation approaches to splat the optical flows (e.g., the first optical flow **406** "$F_{\to1}$" to "t" to obtain the first warped optical flow **508** "$F_{0\to t}$"), which is then used to backward warp the first digital image **402** "I_0" by a backward warping module **510** to obtain the first warped digital image **410** "$I_{0\to t}$." (block **910**). A first warp merge metric is also constructed (block **912**) describing accuracy of respective pixels in the first warped digital image **410**.

[0072] In some instances, splatting leads to visual artifacts that appear as "holes" in a warped result, e.g., due to occlusions, divergent flow fields, and so forth. To address this, the splatting module **506** is configurable to employ a Gaussian kernel **708**. In this instance, a default bilinear kernel **704** having a footprint of "2×2" is replaced with a "4×4" Gaussian kernel **708**. Although such a wider kernel would lead to blurrier results when splatting colors, gaussian kernel **708** does not affect clarity in the techniques described herein in which the splatting module **506** is employed to splat (i.e., forward warp) optical flows to generate the first warped optical flow **508**, which is then backward warped by the backward warping module **510** to generate the first warped digital image **410**.

[0073] Accordingly, the interpolation system **210** is configured to warp the first digital image **402** "I^0" to generate the first warped digital image **410** "$I_{0\to t}$" and the second digital image **404** "I^1" to generate the second warped digital image **414** "$I_{1\to t}$." Rather than averaging these results by the backward warping module **510** (which can cause visual artifacts), the first warp merge metric **412** "$M_{0\to t}{}^{merge}$" and the second warp merge metric **416** "$M_{0\to t}{}^{merge}$" are used as instances of an auxiliary map "M^{merge}" that specifies weights to the individual results before merging them by the synthesis module **216** to obtain the synthesized digital image **218** "I_t" at interpolation instant "t" as:

$$I_t = \frac{(1-t)\cdot M_{0\to t}^{splat}\cdot I_{0\to t} + t\cdot M_{1\to t}^{splat}\cdot I_{1\to t}}{(1-t)\cdot M_{0\to t}^{splat} + t\cdot M_{1\to t}^{splat}}$$

where the first warped digital image **410** "$I_{0\to t}$" is the first digital image **402** "I^0" warped to time "t," "$M_{0\to t}{}^{splat}$" is "$M_0{}^{splat}$" warped to time "t," and analogous for the second warped digital image **414** "$I_{0\to t}$" in the opposite direction.

[0074] FIG. **8** depicts an example implementation **800** of operation of the interpolation system **210** to form the second warped digital image **414** and second warp merge metric **416**. The interpolation system **210** begins in this example by receiving the interpolation instant **204** "t", second digital image **404** "I_1," and second optical flow **408** "$F_{1\to0}$."

[0075] The metric construction module **502** is again employed by the interpolation system **210**, which in this instance is used to generate a second splat metric **802** "$M_1{}^{splat}$." The splatting module **506** then receives the second digital image **404** "I_1," the second splat metric **802** "$M_1{}^{splat}$" and the second merge metric **804** "$M_1{}^{merge}$" as an input. Based on these inputs, the splatting module **506** is configured to generate a second warped optical flow **806** "$F_{1\to t}$" that describes optical flow at the interpolation instant **204** "t" using forward warping. A second warp merge metric **416** is also generated by the splatting module **506** using forward warping as previously described. The backward warping module **510** is again employed, in this instance to form a second warped digital image **414** "$I_{1\to t}$," (block **914**), which is also usable to generate a corresponding second warped merge metric. The synthesis module is then utilized to synthesize a synthesized digital image based on the first warped digital image and the second warped digital image using the first and second warp merge metrics. Although this process has been described for first and second digital images **402**, **404**, this process is repeatable for third digital images by generating a third warped digital image and a third warp merge metric (block **916**), a fourth digital image, and so on that are subsequently combinable by the synthesis module **216** to improve accuracy.

[0076] The warp merge metrics define relative importance of pixels of the warped digital image, which is based on a calculated degree of accuracy and/or confidence in the pixels. This is used to suppress influence of unreliable pixels when generating the synthesized digital image, e.g., to address movement at borders of an object. In this way, the splatting and backward warping techniques support accuracy in generation of the warped digital images and a subsequent synthesized digital image. This is performable without use of conventional refinement techniques typically implemented using neural networks.

Example System and Device

[0077] FIG. **12** illustrates an example system generally at **1200** that includes an example computing device **1202** that is representative of one or more computing systems and/or devices that implement the various techniques described herein. This is illustrated through inclusion of the digital image synthesis system **116**. The computing device **1202** is configurable, for example, as a server of a service provider, a device associated with a client (e.g., a client device), an on-chip system, and/or any other suitable computing device or computing system.

[0078] The example computing device **1202** as illustrated includes a processing system **1204**, one or more computer-readable media **1206**, and one or more I/O interface **1208** that are communicatively coupled, one to another. Although not shown, the computing device **1202** further includes a system bus or other data and command transfer system that couples the various components, one to another. A system bus can include any one or combination of different bus structures, such as a memory bus or memory controller, a peripheral bus, a universal serial bus, and/or a processor or local bus that utilizes any of a variety of bus architectures. A variety of other examples are also contemplated, such as control and data lines.

[0079] The processing system **1204** is representative of functionality to perform one or more operations using hardware. Accordingly, the processing system **1204** is illustrated as including hardware element **1210** that is configurable as processors, functional blocks, and so forth. This includes implementation in hardware as an application specific integrated circuit or other logic device formed using one or more

semiconductors. The hardware elements **1210** are not limited by the materials from which they are formed or the processing mechanisms employed therein. For example, processors are configurable as semiconductor(s) and/or transistors (e.g., electronic integrated circuits (ICs)). In such a context, processor-executable instructions are electronically-executable instructions.

[0080] The computer-readable storage media **1206** is illustrated as including memory/storage **1212**. The memory/storage **1212** represents memory/storage capacity associated with one or more computer-readable media. The memory/storage **1212** includes volatile media (such as random access memory (RAM)) and/or nonvolatile media (such as read only memory (ROM), Flash memory, optical disks, magnetic disks, and so forth). The memory/storage **1212** includes fixed media (e.g., RAM, ROM, a fixed hard drive, and so on) as well as removable media (e.g., Flash memory, a removable hard drive, an optical disc, and so forth). The computer-readable media **1206** is configurable in a variety of other ways as further described below.

[0081] Input/output interface(s) **1208** are representative of functionality to allow a user to enter commands and information to computing device **1202**, and also allow information to be presented to the user and/or other components or devices using various input/output devices. Examples of input devices include a keyboard, a cursor control device (e.g., a mouse), a microphone, a scanner, touch functionality (e.g., capacitive or other sensors that are configured to detect physical touch), a camera (e.g., employing visible or non-visible wavelengths such as infrared frequencies to recognize movement as gestures that do not involve touch), and so forth. Examples of output devices include a display device (e.g., a monitor or projector), speakers, a printer, a network card, tactile-response device, and so forth. Thus, the computing device **1202** is configurable in a variety of ways as further described below to support user interaction.

[0082] Various techniques are described herein in the general context of software, hardware elements, or program modules. Generally, such modules include routines, programs, objects, elements, components, data structures, and so forth that perform particular tasks or implement particular abstract data types. The terms "module," "functionality," and "component" as used herein generally represent software, firmware, hardware, or a combination thereof. The features of the techniques described herein are platform-independent, meaning that the techniques are configurable on a variety of commercial computing platforms having a variety of processors.

[0083] An implementation of the described modules and techniques is stored on or transmitted across some form of computer-readable media. The computer-readable media includes a variety of media that is accessed by the computing device **1202**. By way of example, and not limitation, computer-readable media includes "computer-readable storage media" and "computer-readable signal media."

[0084] "Computer-readable storage media" refers to media and/or devices that enable persistent and/or non-transitory storage of information in contrast to mere signal transmission, carrier waves, or signals per se. Thus, computer-readable storage media refers to non-signal bearing media. The computer-readable storage media includes hardware such as volatile and non-volatile, removable and non-removable media and/or storage devices implemented in a method or technology suitable for storage of information such as computer readable instructions, data structures, program modules, logic elements/circuits, or other data. Examples of computer-readable storage media include but are not limited to RAM, ROM, EEPROM, flash memory or other memory technology, CD-ROM, digital versatile disks (DVD) or other optical storage, hard disks, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or other storage device, tangible media, or article of manufacture suitable to store the desired information and are accessible by a computer.

[0085] "Computer-readable signal media" refers to a signal-bearing medium that is configured to transmit instructions to the hardware of the computing device **1202**, such as via a network. Signal media typically embodies computer readable instructions, data structures, program modules, or other data in a modulated data signal, such as carrier waves, data signals, or other transport mechanism. Signal media also include any information delivery media. The term "modulated data signal" means a signal that has one or more of its characteristics set or changed in such a manner as to encode information in the signal. By way of example, and not limitation, communication media include wired media such as a wired network or direct-wired connection, and wireless media such as acoustic, RF, infrared, and other wireless media.

[0086] As previously described, hardware elements **1210** and computer-readable media **1206** are representative of modules, programmable device logic and/or fixed device logic implemented in a hardware form that are employed in some embodiments to implement at least some aspects of the techniques described herein, such as to perform one or more instructions. Hardware includes components of an integrated circuit or on-chip system, an application-specific integrated circuit (ASIC), a field-programmable gate array (FPGA), a complex programmable logic device (CPLD), and other implementations in silicon or other hardware. In this context, hardware operates as a processing device that performs program tasks defined by instructions and/or logic embodied by the hardware as well as a hardware utilized to store instructions for execution, e.g., the computer-readable storage media described previously.

[0087] Combinations of the foregoing are also be employed to implement various techniques described herein. Accordingly, software, hardware, or executable modules are implemented as one or more instructions and/or logic embodied on some form of computer-readable storage media and/or by one or more hardware elements **1210**. The computing device **1202** is configured to implement particular instructions and/or functions corresponding to the software and/or hardware modules. Accordingly, implementation of a module that is executable by the computing device **1202** as software is achieved at least partially in hardware, e.g., through use of computer-readable storage media and/or hardware elements **1210** of the processing system **1204**. The instructions and/or functions are executable/operable by one or more articles of manufacture (for example, one or more computing devices **1202** and/or processing systems **1204**) to implement techniques, modules, and examples described herein.

[0088] The techniques described herein are supported by various configurations of the computing device **1202** and are not limited to the specific examples of the techniques described herein. This functionality is also implementable

all or in part through use of a distributed system, such as over a "cloud" **1214** via a platform **1216** as described below.

[0089] The cloud **1214** includes and/or is representative of a platform **1216** for resources **1218**. The platform **1216** abstracts underlying functionality of hardware (e.g., servers) and software resources of the cloud **1214**. The resources **1218** include applications and/or data that can be utilized while computer processing is executed on servers that are remote from the computing device **1202**. Resources **1218** can also include services provided over the Internet and/or through a subscriber network, such as a cellular or Wi-Fi network.

[0090] The platform **1216** abstracts resources and functions to connect the computing device **1202** with other computing devices. The platform **1216** also serves to abstract scaling of resources to provide a corresponding level of scale to encountered demand for the resources **1218** that are implemented via the platform **1216**. Accordingly, in an interconnected device embodiment, implementation of functionality described herein is distributable throughout the system **1200**. For example, the functionality is implementable in part on the computing device **1202** as well as via the platform **1216** that abstracts the functionality of the cloud **1214**.

CONCLUSION

[0091] Although the invention has been described in language specific to structural features and/or methodological acts, it is to be understood that the invention defined in the appended claims is not necessarily limited to the specific features or acts described. Rather, the specific features and acts are disclosed as example forms of implementing the claimed invention.

1-20. (canceled)

21. A method comprising:

receiving, by a processing device, a plurality of digital images and a plurality of optical flows describing pixel movement between the plurality of digital images;

generating, by the processing device, a plurality of warped digital images and a plurality of warp merge metrics based on the plurality of digital images and the plurality of optical flows; and

generating, by the processing device, a synthesized digital image by combining the plurality of warped digital images based on the plurality of warp merge metrics.

22. The method as described in claim **21**, wherein the plurality of warp merge metrics defines relative importance of pixels of respective pixels of the plurality of warped digital images based on a parameter.

23. The method as described in claim **22**, wherein the parameter includes photometric consistency, optical flow consistency, or optical flow variance.

24. The method as described in claim **22**, wherein a splat metric defines relative importance of pixels of a respective said warped digital image based on the parameter and is configured to resolve ambiguities caused when multiple pixels map to a same location as part of the generation of the synthesized digital image.

25. The method as described in claim **21**, wherein the plurality of optical flows are produced using a Gaussian kernel.

26. The method as described in claim **21**, further comprising producing the plurality of optical flows using a weight shifting technique in which a maximum pixel value for a plurality of said pixels mapped to a same location is removed from pixel values of the plurality of said pixels.

27. The method as described in claim **21**, wherein the generating the synthesized digital image is generated for an interpolation instant.

28. The method as described in claim **27**, wherein at least one said warped digital image is configured by backward warping.

29. The method as described in claim **21**, further comprising generating at least one said optical flow by:

downsampling a first said digital image and a second said digital image;

estimating a downsampled optical flow based on the downsampled first said digital image and the downsampled second digital said image; and

upsampling the downsampled optical flow using a neural network.

30. The method as described in claim **29**, wherein the upsampling is guided by the first said digital image and a second said digital image.

31. A computing device comprising:

a processing device; and

a computer-readable storage medium storing instructions that, responsive to execution by the processing device, causes the processing device to perform operations including:

receiving a plurality of digital images and a plurality of optical flows describing pixel movement between the plurality of digital images;

generating a plurality of warped digital images and a plurality of warp merge metrics based on the plurality of digital images and the plurality of optical flows; and

generating a synthesized digital image by combining the plurality of warped digital images based on the plurality of warp merge metrics.

32. The computing device as described in claim **31** wherein the plurality of warp merge metrics defines relative importance of pixels of respective pixels of the plurality of warped digital images based on a parameter.

33. The computing device as described in claim **32**, wherein the parameter includes photometric consistency, optical flow consistency, or optical flow variance.

34. The computing device as described in claim **32**, wherein a splat metric defines relative importance of pixels of a respective said warped digital image based on the parameter and is configured to resolve ambiguities caused when multiple pixels map to a same location as part of the generation of the synthesized digital image.

35. The computing device as described in claim **31**, wherein the plurality of optical flows are produced using a Gaussian kernel.

36. The computing device as described in claim **31**, wherein the operations further comprise producing the plurality of optical flows using a weight shifting technique in which a maximum pixel value for a plurality of said pixels mapped to a same location is removed from pixel values of the plurality of said pixels.

37. The computing device as described in claim **31**, wherein the generating the synthesized digital image is generated for an interpolation instant.

38. The computing device as described in claim **37**, wherein at least one said warped digital image is configured by backward warping.

39. One or more computer-readable storage media storing instructions that, responsive to execution by a processing device, causes the processing device to perform operations comprising:

receiving a plurality of digital images and a plurality of optical flows describing pixel movement between the plurality of digital images;

generating a plurality of warped digital images and a plurality of warp merge metrics based on the plurality of digital images and the plurality of optical flows; and

generating a synthesized digital image by combining the plurality of warped digital images based on the plurality of warp merge metrics.

40. The one or more computer-readable storage media as described in claim **39**, wherein the generating the synthesized digital image is generated for an interpolation instant.

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