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# Anamorphic Image Generation Using Hybrid Texture Synthesis

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Anamorphic image is an original image by special distortion, the observer can not get any information from the image at first glance. The original image can be see only the deformation of the image projected back to the specific shape of the mirror surface. Due to anamorphic image presented visual effects is so interesting and attractive, there are lots of artists committed to the anamorphic art invention from the early Renaissance. Different from the general image deformation, artists decorated with small pieces of pattern in the original meaningless anamorphic image, to create a visual double anamorphic art. However, the creation process of anamorphic art would be tedious, the skill always hold to professional artists can not be popular. For the reason, in this paper we propose a semi-automated system, users only need to input an original image and a small image database, the system will automatically analyze the characteristics of original image with a small image, and using the partial shape matching algorithm according to the feature analysis, and automatically selects the matching images to fill the anamorphic image to achieve the artist's decorative skill. Finally, we use the luminance optimization algorithm, adjust the small image's gradation, resulting in the final anamorphic image. The results show that the proposed algorithm not only to maintain the original small image can be recognizable in the anamorphic image but also clearly restore the original image through the ray tracing method to achieve the visual duality anamorphic image.

***Keywords:*** anamorphic, illusion, shape matching, ray tracing, image deformation

## 1. INTRODUCTION

Anamorphosis image is an example of recreational art. Such an image is an art of distorted projection or perspective requiring the viewer to use special devices to reconstitute the image. As an art form, anamorphosis images have been mastered by only a few like István Orosz and Donald Rust. For example, István Orosz specializes in mirror anamorphosis, where a conical or cylindrical mirror (see Fig. 1) is placed on the drawing to transform a flat distorted image into a three dimensional picture that can be viewed from many angles. In Fig. 1, even though an old man is seen on cylindrical mirror via projection, this old man is distorted and hidden on the background.

In recreational art, there are two main types of anamorphosis: perspective and mirror. With mirror anamorphosis, a conical or cylindrical mirror is placed on the drawing or painting to transform a flat distorted image into a three-dimensional picture that can be

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viewed from many angles on the mirror. For example, in Fig. 1, the deformed old man image is painted on a plane surface surrounding the mirror. The original old man image is distorted and hidden on this plane surface with a typically busy apparent image or background and remains imperceptible for a while. It takes targeted effort and conscious focus from the viewer to detect the hidden old man figure. On the other hand, by looking uniquely into the mirror, the old man image appears not deformed and shown in the mirror.

In this paper, we concentrate on generating a mirror type of anamorphic art image. Specially, we propose methods to generate mirror type of anamorphic art results using the natural scene or painting images. We apply a texture method using background natural scene or painting image information to synthesize distorted image of hidden figures according to optimization results of luminance. Fig. 2 shows an anamorphic Monalisa image generated with our methods.

Fig. 1. An anamorphic art created by Donald Rust.

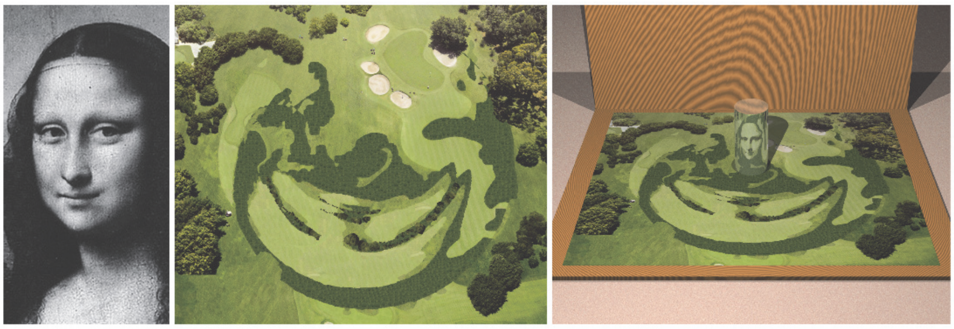


Fig. 2. An example of anamorphic image generated using our system; (a) Monalisa image; (b) Synthesized anamorphic image; (c) The projection of anamorphic image onto a cylindrical reflector presents the Monalisa figure.

## 2. RELATED WORK

Some previous researches have addressed how to automatically design and create optical illusion images using computational tools in computer graphics area. Anamorphosis is also belonging to the field of optical illusion. In the following, we review related work in the field of optical illusion.

In area of optical illusion, some previous work has focused on generating illusory motions in the plane. Kitaoka *et al.* [1] apply the combinations of certain color patterns to produce illusion effect. Wei [2] proposes an automatic method to visualize vector fields using tile-based RAPs (repeated asymmetric patterns). Furthermore, Chi *et al.* [3] propose an automatic streamline and RAP based method to generate self-animating images. Examples generated are shown to evidence the illusory effect and the potential applications for entertainment and design purposes.

Mitra *et al.* [4] present a synthesis technique to generate emerging images from a given scene. A procedure that synthesizes emergence images can be an effective tool for exploring and understanding the factors affecting computer vision techniques. Later, Chu *et al.* [5] apply a texture synthesis technique to create camouflage images with natural appearance. Camouflage images can be also seen as a form of optical illusion art and contain one or more hidden figures that remain imperceptible or unnoticed for a while. Recently, Du *et al.* [6] present an alternative approach to create digital camouflage images by following human's perception intuition and compiling with the physical creation procedure of artists. Their camouflage images are natural and have less long coherent edges in the hidden region.

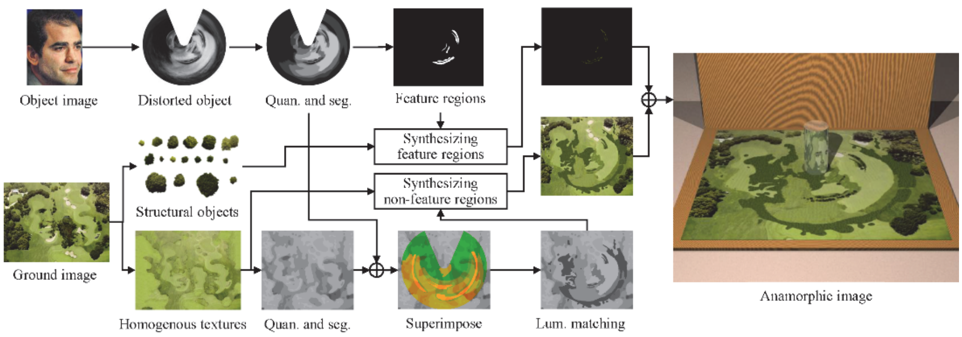


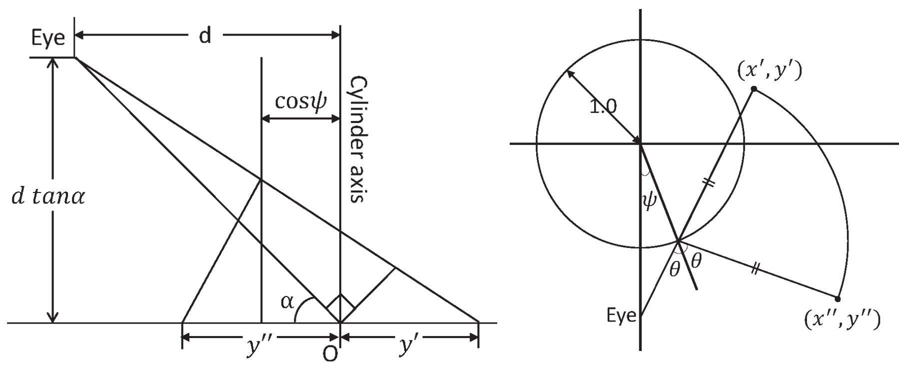

Fig. 3. System overview.

## 3. OVERVIEW

Our algorithm to create an anamorphic image is mainly inspired by the art work of Donald Rust (see Fig. 1). The artist skillfully conceals a distorted target object in a seemingly normal image (*e.g.*, the ground with leaves) that presents clear figure of the hidden object (*e.g.*, an old man) when viewing its mirrored image on a reflector (*e.g.*, the cylinder). More specifically, distinct structural objects (*e.g.*, leaves) are used to represent salient features of object (*e.g.*, eyes and beard) while the monotonic regions (*e.g.*, cheek and forehead) are covered with homogenous textures (*e.g.*, dust). To mimic such a special procedure of creating anamorphic art, we propose a semi-automatic algorithm to create the anamorphic images in two stages that synthesizes *feature* and *non-feature* regions of object image using structural and flat textures extracted from a scenery image, respectively. Fig. 3 illustrates the workflow of our system.

The inputs to our system are a target object image to be presented on a cylindric reflector and a ground image where the distorted object image would be placed. The object image is first warped using the inverse cylindric projection proposed by Hunt *et al.* [7] and a highly distorted object image is generated (Section 4.1). We quantize and segment the distorted object image into segments which are further classified into feature and non-feature parts according to the strokes prescribed by users on the original image. The generation of anamorphic images is formulated as synthesizing the distorted object image using textures from the ground image, leading to a seemingly normal scenery image that presents the object image on a cylindric reflector.

To this end, we utilize the rich context from the input ground image by manually extracting structural objects (*e.g.*, trees and houses) from homogenous regions. Since the feature segments play a crucial role in perceiving object image, we use the extracted structural objects to fill up these segments (Section 4.3). As for the non-feature segments which correspond to monotonic regions in the object image, we first quantize and segment the homogenous regions of a ground image and adopt a luminance matching to obtain a correspondence between object and ground segments. Then a texture-by-number technique is used to synthesize the non-feature segments (Section 4.4). The effectiveness of our algorithm is demonstrated using several visually convincing and entertaining anamorphic images.




(a) A side view. (b) A top view.

Fig. 4. The geometry of the anamorphic warping based on cylindric reflector.

## 4. ALGORITHM

### 4.1 Anamorphic Warping

To generate a warped object image such that the original image content is restored when the image is projected onto a cylindric reflector, we adopt a ray tracing approach to simulate the anamorphic projection. Fig. 4 illustrates the geometry of ray tracing between a cylinder and a ground plane. Assume the cylinder has an unit radius, then given a point $(x, y)$ on the viewing plane, we compute it's reflected point on the ground, $(x'', y'')$, using the following equations:

$$x'' = x' + \frac{2x'}{d + y'}(\cos\ \Psi + y')(d \cos\ \Psi - 1)$$
$$y'' = -y' + 2\cos\ \Psi(\cos\ \Psi + y')\left(\frac{d \cos\ \Psi - 1}{d - \cos\ \Psi}\right) \tag{1}$$

with

$$\cos\Psi = \frac{dx'^2 + (d + y')\sqrt{d^2(1 - x'^2) + 2dy' + x'^2 + y'^2}}{(d + y')^2 + x'^2}$$
$$x' = x\left(\frac{d + y'}{d}\right) \tag{2}$$
$$y' = \frac{y / \sin\alpha}{1 - (y/(d \tan\alpha))\cos\alpha},$$

where $(x', y')$ is the intersection of ray which passes through the cylinder with the ground. Both $\alpha$ and $d$ are parameters indicating the elevation and horizontal distance of viewing point with respect to the cylinder. Please refer [7] for more details.

An example image is shown in Fig. 5. As we can see that although the original object image is highly distorted under the anamorphic warping, it still reveals, to some degrees, the original image contents (*e.g.*, eyes and mouse), thus rendering a naive blending with ground image infeasible. Next, we will elaborate a novel algorithm to synthesize anamorphic images using textures from ground image, guiding by the image contents of distorted object image.

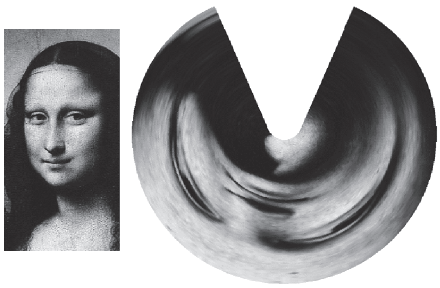


Fig. 5. An example of anamorphic warping.

### 4.2 Ground Image Preprocessing

Given a ground image, we manually decompose its texture into two parts, the structural objects and flat textures that are used to synthesize salient features and monotonic regions of object image, respectively. To extract structural objects from the ground image, we utilize a convenient and effective image segmentation tool, GrabCut [8], to cut out structural objects and denote them as $D=\{o_1, ..., o_n\}$. Removing structural objects result in holes in the ground image. We further apply the state-of-the-art image completion algorithm, the PatchMatch [9], to automatically fill up the holes, producing an image with only flat and homogenous textures and is denoted as $I_b$. Note that such preprocess only needs to be done once for each input ground image and can be reused to synthesize arbitrary object images. Fig. 6 shows an example of structural and flat textures extraction.

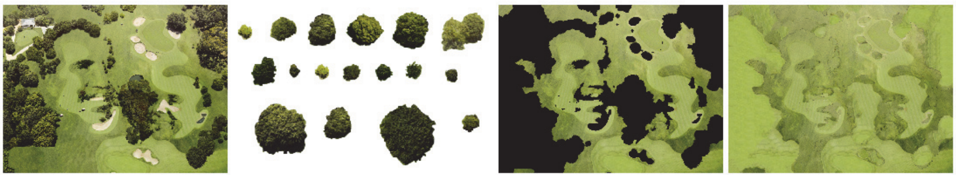


Fig. 6. (a) A ground image; (b) Structural objects; (c) Flat textures; (d) Holes in (c) are filled via image completion.

### 4.3 Synthesizing Feature Regions

Some image features such as the facial features are important cues for human to perceive the shape of image content. However, it remains a challenge in computer vision to automatically identify and extract such semantic features. To specify salient regions on object image, we provide the user a drawing tool, allowing him or her to scribble on the object image. Those strokes are warped and attached to distorted object image as well. Then we convert the distorted object to grayscale and apply an image quantization to obtain a collection of disjoint image segments. Those segments which are overlapping with user-defined strokes are labeled as feature segments while the remaining parts are non-feature segments.

To synthesize feature segments, we formulate the problem as solving a 2D image college where the goal is to pack the interior areas of feature segments using textures of structural objects, $D$. However, due to nature of anamorphic warping, feature segments are usually long, narrow and curve shapes, posing a severe constraint to pack structural objects which are nearly squared shapes. To address this problem, we employ a greedy approach to subdivide the interior areas of feature segments into nearly squared regions. For each feature segment, we first extract its skeleton using image thinning. Then, we define a line segment at each interior skeletal joint that is orthogonal to the incident skeletal edge and intersects with the contour of segments at both sides of the skeleton. Starting from the end point of the skeleton, we iteratively go through each skeleton joint, and compare the length of visited skeletal edge and the current horizontal line segment. If the difference of length is less than a threshold, we divide the segment into a disjoint region using the line segment. Such approach, although simple, could efficiently and effectively divide the feature segments into near squared shapes which are suitable for packing structural objects (see Fig. 7 (b)).

The shape of subdivided segments might still be significantly different from those of structural objects in terms of size and orientation. To account for such variation, we search an optimal structural object for each subdivided region such that the following equation is minimized:

$$\min_{o_i, T_i}\{-P_I(o_i, T_i) + \lambda_1 P_O(o_i, T_i) + \lambda_2 P_W(o_i, T_i)\}, \tag{3}$$

where $o_i$ and $T_i$ are structual object and optimal affine transformation (rotation, translation and uniform scaling), while $P_I(\cdot)$ measures the overlapping area of $o_i$ with segment region, $P_W(\cdot)$ and $P_O(\cdot)$ represent the area that falls outside the region and overlaps with neighboring regions, respectively. $\lambda_1$ and $\lambda_2$ are parameters that control the relative weight between $P_O(\cdot)$ and $P_W(\cdot)$, and we use $\lambda_1$=$\lambda_2$=1.0 for all the results shown in this paper. Fig. 7 (c) shows results of packing feature segments with structural objects.

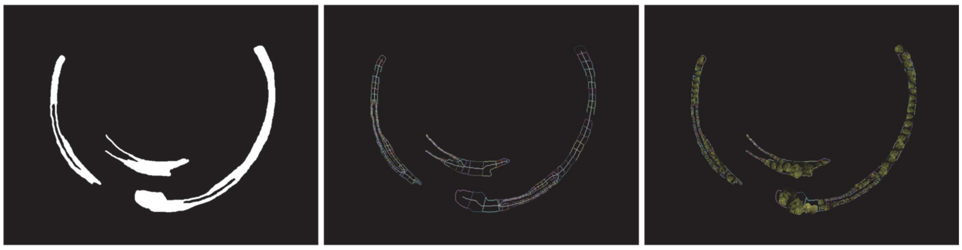


Fig. 7. (a) Feature segments; (b) Skeleton (white line) and subdivided area of feature segments; (c) Image packing with structural objects.

### 4.4 Synthesizing Non-Feature Regions

As for the non-feature segments which correspond to monotonic regions of object image, we use the homogenous textures of ground image to synthesize those segments and obtain the final anamorphic image. We adopt a texture-by-number technique to first establish a correspondence between object segment and a part of ground image which in turn provides texture examplars to synthesize the segment. In another word, we employ an approach similar to Chu *et al.* [5] who attempted to seamlessly camouflage an object into a background image.

**Quantization and Segmentation** Specifically, we first convert the preprocessed ground image $I_b$ into grayscale image and quantize the image in the same manner as we apply to object image. We denote the luminance values of the quantized $I_b$ as $Q_b = \{q_1^b, \ldots, q_m^b\}$. Next, we superimpose the non-feature segments with the quantized $I_b$ and jointly segment both the non-feature segments from object image and quantized ground image $I_b$. We denote the segmentation as $L_S = \{(l_1^F, \ldots, l_1^B), \ldots, (l_m^F, \ldots, l_m^B)\}$, where $l_1^F$, and $l_1^B$ indicate the luminance value from object and ground image, respectively.

**Graph Construction** We construct a graph $G = (V, E)$ with nodes $v_i \in V$ correspond to segments in $L_S$. If two nodes $v_i$ and $v_j$ are adjacent and have shared boundary, we add an edge $(i, j) \in E$. To establish a correspondence between each subdivided non-feature segment and ground image, we formulate the problem as assigning a set of new luminance values $L'_S = \{(l'_1, \ldots, l'_m)\}$, to each $v_i \in V$ by optimizing an objective function consisting of two terms, *self-similarity* and *contrast-preserving*.

**Energy Formulation** In the context of self-similarity, we formulate an energy term to measure how well the new luminance value of each segment is close to its original value. As segments may have different sizes and shapes, we account for such differences by weights as:

$$E_S(L'_S) = \sum_{v_i \in V} w_i \{W_F \, | l'_i - l_i^F \, | + W_B \, | l'_i - l_i^B \, |\}, \tag{4}$$

where $w_i$ is area of segment $v_i$, and $W_F$ and $W_B$ are relative weight for keeping the luminance from object or ground image, respectively. As for the contrast-preserving term, the idea is to retain the original contrasts between adjacent segments and the energy is defined as follows:

$$E_C(L'_S) = \sum_{\substack{(v_i, v_j) \in E, \\ l'_i \neq l'_j}} w_{i,j} \{W_F \, | (l'_i - l'_j) - (l_i^F - l_j^F) \, | + W_B \, | (l'_i - l'_j) - (l_i^B - l_j^B) \, |\}, \tag{5}$$

where $w_{i,j}=(b_{i,j}\, a_i+b_{j,i}\, a_j)/2$ and $b_{i,j}$ is the length of shared boundary between $v_i$ and $v_j$. The $a_i$ is area size of segment $v_i$.

**Optimization:** Given the two energy terms, we define the total energy and the optimization as:

$$L'_S = \arg\min_{l'_i \in Q_b} \{\lambda E_S(L'_S) + (1.0 - \lambda) E_C(L'_S)\}, \tag{6}$$

where $\lambda$ controls the relative importance of $E_S$ and $E_C$, and is set to 0.5 across all experiments. To minimize above energy, we use a multi-label graph cut algorithm [10-12] that uses the $\alpha - \beta$ swap algorithm to simultaneously change the values among nodes and effectively approximate the global minimum. In our experiments, it takes less than 2 seconds to synthesize an image of moderate size. Fig. 8 (b) shows an example of optimized luminance assignment.

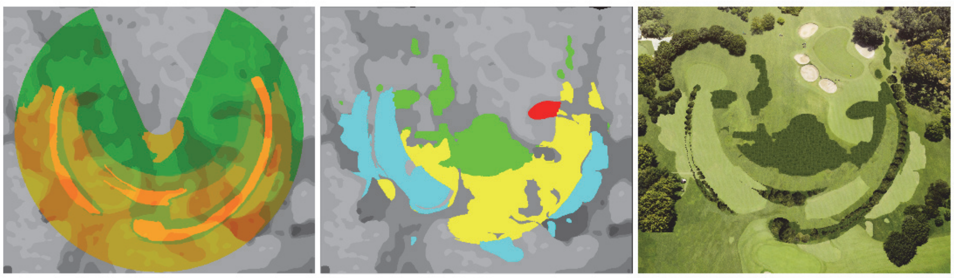


Fig. 8. (a) Overlapped object and ground segments; Only the colour regions are involved in the luminance optimization; (b) Colour segments indicate holes need to be completed via PatchMatch, where different colors represent different texture sources; (c) The synthesized result.

**Texture Synthesize** To synthesize the segments based on the optimal luminance correspondence, we adopt the PatchMatch [9] in a manner that considers the segments as empty holes and attempts to use textures from corresponding ground segments to complete these holes. Specifically, consider the following scenarios: (i) if a segment $l'_i = l^B_i$, we directly copy the textures from underlying ground segment. (ii) if a segment $l'_i \neq l^B_i$, we set label correspondence between segment $l'_i$ and a quantized ground segment that has the same luminance as $l'_i$. After establishing all the label correspondence of target segments, we perform the PatchMatch to do the image completion and obtain the synthesized non-featured regions. Finally, we compose the resultant anamorphic image by combining synthesized feature and non-feature images.

## 5. RESULTS

We have implemented our system on a moderate computer with Intel i7-2600 CPU, and 8GB DDR3 RAM. In average, our system takes less than 1 minute to generate an anamorphic image and the time complexity is mainly affected by the number and size of non-feature segments that were completed via PatchMatch. In Fig. 9, we show eight anamorphic images generated by our system. To simulate the anamorphic image on a cylindric reflector in real world scenario, we model a virtual environment and use the ray-tracing to render the result. Our anamorphic image, when observed from a top-view, presents just a normal scenery image while the figure of hidden object image can be clearly presented when it is projected to the cylindric reflector. Such strong perception of visual duality demonstrates the effectiveness of our system.

**Limitations** We currently assume the structural objects are of squared shapes. Therefore, it requires special treatment for objects with more complex shapes. For instance, the input ground image used to synthesize the results shown in Fig. 9 (2nd column) is Fig. 10 where the "houses" are extracted as structural objects. Due to the general city view where the houses are normally aligned and cannot vary significantly with neighbors in size, we need to apply additional constraints on finding the optimal affine transformation in Eq. (3) (*e.g.*, with limited range of rotation and scaling, and neighboring buildings should align with each other).

Fig. 10. Input image used to synthesize results shown in Fig 9.

Another key factor to an effective anamorphic image is that the ground image contains sufficient luminance various such that the system could extract proper textures used to synthesize non-feature regions of object image. Otherwise, the original contrast among object segments might be damaged and result in unclear projection on the cylindric reflector.

## 6. CONCLUSION AND FUTURE WORK

Anamorphic image is a kind of illusory art which is visually appealing entertaining. In this paper, we present a semi-automatic algorithm to generate the anamorphic image by composing one object image with another scenery image through a hybrid texture synthesis approach. We demonstrate using several results that our system is not only able to generate effective anamorphic images in a few minutes. It also presents a useful tool for regular popularity to create their own anamorphic images and for artists to initialize their artwork and dedicate in creativity design.

There are several interesting future avenues worth investigating. Rather using only cylindric reflector, other shapes of reflector (*e.g.*, pyramid) could be potential fascinating designs. To handle a structural object with complex shape, it requires more sophisticated packing algorithm. Previous works on image mosaics [3] could be potential substitutions.

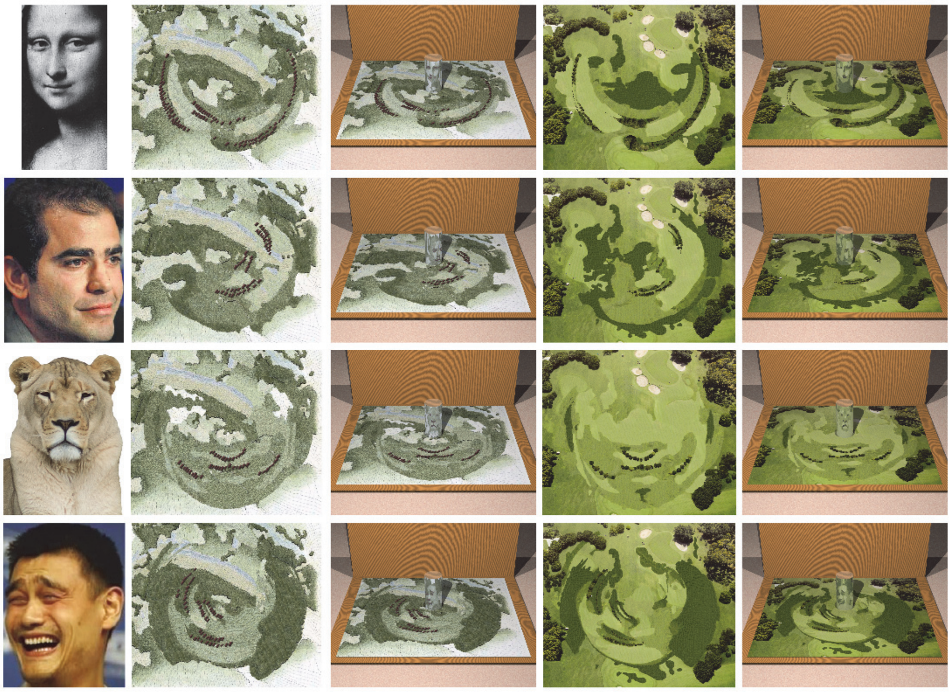


Fig. 9. Anamorphic images generated by our system. *1st* column are input object images. *2nd* and *4th* columns represent synthesized anamorphic images, and *3rd* and *5th* columns are corresponding ray tracing results. Note that the synthesized images are seemingly normal scenery images while their projection on the reflector present clear figures of target objects, showing strong anamorphic illusion.

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