# A Generalized Morphological Skeleton Transform Using both Internal and External Skeleton Points 

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#### Abstract

The morphological skeleton transform (MST) is a leading morphological shape representation scheme. In the MST, a given shape is represented as a union of all maximal disks contained in the shape. The concepts of external skeleton points and external maximal disks were introduced recently to derive so-called external shape components for shape matching purposes. In this paper, we develop a generalized morphological skeleton transform that combines the concepts of internal and external maximal disks into a unified framework. In this framework, a shape is described in terms disk components that need to be added as well as disk components that need to be removed. This framework provides a more natural way of modeling the approximation and reconstruction of binary shapes.


Keywords: mathematical morphology, shape representation, skeleton transform, shape approximation, shape reconstruction

## 1 Introduction

Shape representation is an important issue in image analysis and computer vision. Efficient shape representation provides the foundation for the development of efficient algorithms for many shape-related processing tasks such as image coding, shape matching and recognition, contentbased video processing, and image data retrieval.

Mathematical morphology is a shape-based approach to image processing. A number of morphological shape representation algorithms have been proposed [1-8]. The morphological skeleton transform (MST) is a leading morphological shape representation scheme [1]. In the MST, a given shape is represented as a union of all maximal disks contained in the shape. The advantages of the MST include that it has a simple and intuitive mathematical characterization as well as easy and efficient implementations. Some shape matching algorithms have been developed based on the MST $[9,10]$.

In a recent paper, we developed a structural shape matching algorithm that uses both internal and external shape components [11]. The internal shape components are selected from the internal maximal disks determined by a traditional MST. The external shape components are
selected from the external maximal disks determined by a separate "external" skeleton transform.

In this paper, we develop a generalized morphological skeleton transform that combines the concepts of internal and external maximal disks into a unified framework. In this framework, a shape is described in terms disk components that need to be added as well as disk components that need to be removed. The positive (addition) and negative (removal) steps are applied alternately to derive the final representation of the input shape.

## 2 Internal and External Skeleton Transforms

We first review the standard skeleton transform. For a shape image $X$ and a structuring element $B$, which is used as the unit disk, if we define size- $i$ disk $i B$ as $i B=B \oplus B \oplus \ldots \oplus$ $B$ ( $i \quad$ 's), then $X$ can be expressed as the union of all maximal disks contained in $X$ :

$$
\begin{align*}
X= & \left(S_{N} \oplus N B\right) \cup\left(S_{N-1} \oplus(N-1) B\right) \cup \ldots \cup\left(S_{2} \oplus 2 B\right) \\
& \cup\left(S_{1} \oplus B\right) \cup S_{0} \tag{1}
\end{align*}
$$

where

$$
\begin{equation*}
S_{i}=(X \ominus i B) \backslash((X \ominus i B) \circ B) \tag{2}
\end{equation*}
$$

and $N$ is the largest integer such that $X \ominus N B \neq \emptyset$. Each $S_{i}$ is called a skeleton subset of order $i$. Each skeleton point in $S_{i}$ represents a maximal disk of size $i$ contained in $X$. A smoothed (or approximate) version of $X$ can be reconstructed if some lower order skeleton subsets are omitted:

$$
\begin{align*}
X \circ k B= & \left(S_{N} \oplus N B\right) \cup\left(S_{N-1} \oplus(N-1) B\right) \cup \ldots \\
& \cup\left(S_{\mathrm{k}+1} \oplus(\mathrm{k}+1) B\right) \cup\left(S_{\mathrm{k}} \oplus k B\right), \text { for } k \leq N . \tag{3}
\end{align*}
$$

We can also write

$$
\begin{align*}
X \circ k B= & (X \circ n B) \cup\left(S_{n-1} \oplus(n-1) B\right) \cup \ldots \cup \\
& \left(S_{k+1} \oplus(k+1) B\right) \cup\left(S_{k} \oplus \mathrm{k} B\right), \text { for } k<n \leq N . \tag{4}
\end{align*}
$$

A more accurate approximation $X \circ k B$ for $X$ can be obtained from a rougher approximation $X \circ n B$ by adding additional maximal disks.

We now review the concept of external skeleton points. For the unit disk $B$, the reflection of $B$ is defined as

$$
\begin{equation*}
B^{R}=\{b \mid-b \in B\} . \tag{5}
\end{equation*}
$$

For a shape image $X$ and the unit disk $B$, since closing operation is extensive, we have


Fig. 1. Three simple shapes.

$$
\begin{align*}
X & =\left(X \bullet B^{R}\right) \backslash T_{0}=\left(\left(X \oplus B^{R}\right) \ominus B^{R}\right) \backslash T_{0} \\
& =\left(X_{1} \ominus B^{R}\right) \backslash T_{0} \tag{6}
\end{align*}
$$

where

$$
\begin{gather*}
T_{0}=\left(X \bullet B^{R}\right) \backslash X  \tag{7}\\
X_{1}=X \oplus B^{R} . \tag{8}
\end{gather*}
$$

Now we can also write

$$
\begin{equation*}
X_{1}=\left(X_{1} \bullet B^{R}\right) \backslash T_{1} \tag{9}
\end{equation*}
$$

where

$$
\begin{equation*}
T_{1}=\left(X_{1} \bullet B^{R}\right) \backslash X_{1}=\left(\left(X \oplus B^{R}\right) \bullet B^{R}\right) \backslash\left(X \oplus B^{R}\right) \tag{10}
\end{equation*}
$$

Combining (6) with (9), we have

$$
\begin{align*}
X & =\left(\left(\left(X_{1} \bullet B^{R}\right) \backslash T_{1}\right) \ominus B^{R}\right) \backslash T_{0} \\
& =\left(\left(X_{1} \bullet B^{R}\right) \ominus B^{R}\right) \backslash\left(T_{1} \oplus B\right) \backslash T_{0} \\
& =\left(\left(\left(\left(X \oplus B^{R}\right) \oplus B^{R}\right) \ominus B^{R}\right) \ominus B^{R}\right) \backslash\left(T_{1} \oplus B\right) \backslash T_{0} \\
& =\left(X \bullet 2 B^{R}\right) \backslash\left(T_{1} \oplus B\right) \backslash T_{0} . \tag{11}
\end{align*}
$$

Each point in $T_{0}$ represents a point that is not in $X$ and each point $p$ in $T_{1}$ represents a disk $p \oplus B$ that is not in $X$. Removing all such points and disks results in the restoration of $X$ from $X \bullet 2 B^{R}$. Repeating similar steps, we have

$$
\begin{align*}
X= & \left(X \bullet m B^{R}\right) \backslash\left(T_{m-1} \oplus(m-1) B\right) \backslash\left(T_{m-2} \oplus(m-2) B\right) \backslash \ldots \\
& \backslash\left(T_{1} \oplus B\right) \backslash T_{0} \tag{12}
\end{align*}
$$

where

$$
\begin{equation*}
T_{i}=\left(\left(X \oplus i B^{R}\right) \bullet B^{R}\right) \backslash\left(X \oplus i B^{R}\right) \tag{13}
\end{equation*}
$$

The points in $T_{m-1}, T_{m-2}, \ldots T_{1}, T_{0}$ can be viewed as external skeleton points and they represents external disks of different sizes. Removal of such disks results in the restoration of $X$ from $X \bullet m B^{R}$. In fact, these external disks are maximal disks contained in the background shape, or the complement of $X$. This transform can be viewed as an external skeleton transform. A partially restored $X$ can be created if some lower order skeleton subsets are omitted:

$$
\begin{align*}
X \bullet k B^{R}= & \left(X \bullet m B^{R}\right) \backslash\left(T_{m-1} \oplus(m-1) B\right) \backslash \ldots \\
& \backslash\left(T_{k+1} \oplus(k+1) B\right) \backslash\left(T_{\mathrm{k}} \oplus k B\right), \text { for } k<m . \tag{14}
\end{align*}
$$

A better approximation $X \bullet k B^{R}$ for $X$ is obtained from a rougher approximation $X \bullet m B^{R}$ by removing external maximal disks.

## 3 Generalized Skeleton Transform

It is clear that a shape cannot be completely specified using external skeleton points only. The closed version $X$
$m B^{R}$ of $X$ in (12) in general will grow bigger as $m$ increases. We can use a number of internal skeleton points to represent $X \bullet m B^{R}$. Any finite shape can be completely specified using internal skeleton points only. However, sometimes it is more efficient to describe a shape using both internal and external skeleton points. Consider the shape in Fig. 1(a). This is a near circular shape (in digital sense). Therefore, there is an efficient representation for it using internal skeleton points only. Now look at the shape in Fig. 1(b). This is the same circular shape with a near circular hole in it. If we still only use internal skeleton points, then we will need a lot more skeleton points to describe the areas between internal and external boundaries. If we can use external skeleton points to describe the hole first, then we can still use the initial efficient internal skeleton representation for the overall circular shape. Now we consider the shape in Fig. 1(c). The hole on the object has been cut into two halves. To represent two separate holes, we will need to use more external skeleton points. But if we can describe the small line segment that separates the original hole using some positive skeleton points first, then the more efficient representation for the original hole can still be used as part of the overall description. In this section, we develop a generalized skeleton transform that takes this hierarchical and alternately positive and negative description approach.

For a given shape image $X$ and an structuring element $B$ which is used as the unit disk, we can write

$$
\begin{equation*}
X=(X \circ B) \cup S_{0}=X^{\prime} \cup S_{0} \tag{15}
\end{equation*}
$$

where

$$
\begin{gather*}
X^{\prime}=X \circ B,  \tag{16}\\
S_{0}=X \backslash(X \circ B) . \tag{17}
\end{gather*}
$$

In (15), $X^{\prime}$ can be viewed as a smoothed version of $X$ and $S_{0}$ is a positive skeleton subset. For $X^{\prime}$ we can write

$$
\begin{equation*}
X^{\prime}=\left(X^{\prime} \bullet B^{R}\right) \backslash T_{0}=X_{1} \backslash T_{0} \tag{18}
\end{equation*}
$$

where

$$
\begin{gather*}
X_{1}=X^{\prime} \bullet B^{R}  \tag{19}\\
T_{0}=\left(X^{\prime} \bullet B^{R}\right) \backslash X^{\prime} \tag{20}
\end{gather*}
$$

In (18), $X_{1}$ can be viewed as a smoothed version of $X^{\prime}$ and $T_{0}$ is a negative skeleton subset. Combining (15) and (18), we get


Fig. 2. An example showing that $X_{1} \neq X_{1} \circ 2 B \cup S_{1} \oplus B$ : (a) Image $X$; (b) Unit disk $B$; (c) $X^{\prime}=X \circ B$; (d) $X_{1}=X^{\prime} \bullet B^{R}$; (e) $X_{1} \circ 2 B \cup S_{1} \oplus B$.

$$
\begin{equation*}
X=X_{1} \backslash T_{0} \cup S_{0} \tag{21}
\end{equation*}
$$

We assume that we perform set-theoretical operations from left to right. $X_{1}$ can also be viewed as a smoothed version of $X$ and both positive and negative skeleton subsets are used to represent $X$ now. For $X_{1}$ in (21), we have

$$
\begin{equation*}
X_{1} \approx X_{1} \circ 2 B \cup S_{1} \oplus B=X_{1}^{\prime} \cup S_{1} \oplus B \tag{22}
\end{equation*}
$$

where

$$
\begin{gather*}
X_{1}^{\prime}=X_{1} \circ 2 B  \tag{23}\\
S_{1}=X_{1} \ominus B \backslash X_{1} \ominus B \circ B \tag{24}
\end{gather*}
$$

We assume that we perform morphological operations from left to right and we perform morphological operations before set-theoretical operations. In (22), $X_{1}{ }^{\prime}$ is a smoothed version of $X_{1}$ and $S_{1}$ is a positive skeleton subset. Note that, in general, $X_{1} \neq X_{1} \circ 2 B \cup S_{1} \oplus B=X_{1} \circ B$. An example showing this inequality is given in Fig. 2. Combining (21) and (22), we get an approximation for $X$ :

$$
\begin{equation*}
X \approx X_{1}^{\prime} \cup S_{1} \oplus B \backslash T_{0} \cup S_{0} \tag{25}
\end{equation*}
$$

Now we have an approximation for $X$ using a smoothed version $X_{1}{ }^{\prime}$ and a number of skeleton subsets. In the next step, we use closing again. For $X_{1}{ }^{\prime}$ in (25), we have

$$
\begin{equation*}
X_{1}^{\prime} \approx X_{1}^{\prime} \bullet 2 B^{R} \backslash T_{1} \oplus B=X_{2} \backslash T_{1} \oplus B \tag{26}
\end{equation*}
$$

where

$$
\begin{gather*}
X_{2}=X_{1}^{\prime} \bullet 2 B^{R}  \tag{27}\\
T_{1}=X_{1}^{\prime} \oplus B^{R} \bullet B^{R} \backslash X_{1}^{\prime} \oplus B^{R} \tag{28}
\end{gather*}
$$

Notice also that in general we have $X_{1}{ }^{\prime} \neq X_{1}{ }^{\prime} \bullet 2 B^{R} \backslash T_{1} \oplus B$ $=X_{1}{ }^{\prime} \bullet B^{R}$. In (26), we have a smoothed version $X_{2}$ and a negative skeleton subset $T_{1}$. Combining (25) and (26), we have a new approximation:

$$
\begin{equation*}
X \approx X_{2} \backslash T_{1} \oplus B \cup S_{1} \oplus B \backslash T_{0} \cup S_{0} \tag{29}
\end{equation*}
$$

In order to see a pattern, we develop two more steps. The next approximation step uses an opening operation and a positive skeleton subset:

$$
\begin{equation*}
X_{2} \approx X_{2} \circ 3 B \cup S_{2} \oplus 2 B=X_{2}^{\prime} \cup S_{2} \oplus 2 B \tag{30}
\end{equation*}
$$

where

$$
\begin{gather*}
X_{2}^{\prime}=X_{2} \circ 3 B  \tag{31}\\
S_{2}=X_{2} \ominus 2 B \backslash X_{2} \ominus 2 B \circ B \tag{32}
\end{gather*}
$$

A new approximation containing the new skeleton subset is

$$
\begin{equation*}
X \approx X_{2}{ }^{\prime} \cup S_{2} \oplus 2 B \backslash T_{1} \oplus B \cup S_{1} \oplus B \backslash T_{0} \cup S_{0} \tag{33}
\end{equation*}
$$

The next approximation step uses a closing operation and a negative skeleton subset:

$$
\begin{equation*}
X_{2}^{\prime} \approx X_{2}^{\prime} \bullet 3 B^{R} \backslash T_{2} \oplus 2 B=X_{3} \backslash T_{2} \oplus 2 B \tag{34}
\end{equation*}
$$

where

$$
\begin{gather*}
X_{3}=X_{2}^{\prime} \bullet 3 B^{R}  \tag{35}\\
T_{2}=X_{2}^{\prime} \oplus 2 B^{R} \bullet B^{R} \backslash X_{2}^{\prime} \oplus 2 B^{R} \tag{36}
\end{gather*}
$$

A new approximation containing the new skeleton subset is $X \approx X_{3} \backslash T_{2} \oplus 2 B \cup S_{2} \oplus 2 B \backslash T_{1} \oplus B \cup S_{1} \oplus B \backslash T_{0} \cup S_{0}$

In general, with

$$
\begin{equation*}
X \approx X_{i} \backslash T_{i-1} \oplus(i-1) B \cup S_{i-1} \oplus(i-1) B \backslash \ldots \backslash T_{0} \cup S_{0} \tag{37}
\end{equation*}
$$

we use

$$
\begin{equation*}
X_{i} \approx X_{i} \circ(i+1) B \cup S_{i} \oplus i B=X_{i}^{\prime} \cup S_{i} \oplus i B \tag{38}
\end{equation*}
$$

where

$$
\begin{gather*}
X_{i}^{\prime}=X_{i} \circ(i+1) B  \tag{40}\\
S_{i}=X_{i} \ominus i B \backslash X_{i} \ominus i B \circ B
\end{gather*}
$$

A new approximation for $X$ containing $S_{i}$ is

$$
\begin{align*}
X \approx & X_{i}^{\prime} \cup S_{i} \oplus i B \backslash T_{i-1} \oplus(i-1) B \cup S_{i-1} \oplus(i-1) B \backslash \ldots  \tag{41}\\
& \backslash T_{0} \cup S_{0} \tag{42}
\end{align*}
$$

We also use

$$
\begin{equation*}
X_{i}^{\prime} \approx X_{i}^{\prime} \bullet(i+1) B^{R} \backslash T_{i} \oplus i B=X_{i+1} \backslash T_{i} \oplus i B \tag{43}
\end{equation*}
$$

where

$$
\begin{gather*}
X_{i+1}=X_{i}^{\prime} \bullet(i+1) B^{R}  \tag{44}\\
T_{i}=X_{i}^{\prime} \oplus i B^{R} \bullet B^{R} \backslash X_{i}^{\prime} \oplus i B^{R} \tag{45}
\end{gather*}
$$

A new approximation including the latest skeleton subset is

$$
\begin{align*}
X \approx & X_{i+1} \backslash T_{i} \oplus i B \cup S_{i} \oplus i B \backslash T_{i-1} \oplus(i-1) B \cup S_{i-1} \\
& \oplus(i-1) B \backslash \ldots \backslash T_{0} \cup S_{0} \tag{46}
\end{align*}
$$

Eventually, we will encounter a $N$ such that $X_{N}{ }^{\prime}=X_{N} \circ$ $(N+1) B=\emptyset$ with $X_{N} \neq \emptyset$. This implies that $X_{N} \ominus(N+1) B=$ $\emptyset$. And from this, we can see that $S_{N}=X_{N} \ominus N B$. It is also easy to see that $T_{N}=\emptyset$ and $X_{n}=X_{n}{ }^{\prime}=\emptyset$ for $n \geq N+1$. So the final approximation is

$$
X \approx S_{N} \oplus N B \backslash T_{N-1} \oplus(N-1) B \cup S_{N-1} \oplus(N-1) B \backslash \ldots
$$

$$
\begin{equation*}
\backslash T_{0} \cup S_{0} \tag{47}
\end{equation*}
$$

We have obtained a series of approximations for $X$. The final approximation uses a sequence of alternately positive and negative skeleton subsets. These skeleton subsets are obtained from progressively smoothed versions of $X$. We now claim that all these approximations are in fact exact representations of $X$ :

$$
\begin{align*}
X & =X^{\prime} \cup S_{0} \\
& =X_{1} \backslash T_{0} \cup S_{0} \\
& =X_{1}{ }^{\prime} \cup S_{1} \oplus B \backslash T_{0} \cup S_{0} \\
& =X_{2} \backslash T_{1} \oplus B \cup S_{1} \oplus B \backslash T_{0} \cup S_{0} \\
& =X_{2}{ }^{\prime} \cup S_{2} \oplus 2 B \backslash T_{1} \oplus B \cup S_{1} \oplus B \backslash T_{0} \cup S_{0} \\
& =X_{3} \backslash T_{2} \oplus 2 B \cup S_{2} \oplus 2 B \backslash T_{1} \oplus B \cup S_{1} \oplus B \backslash T_{0} \cup S_{0} \\
& \cdots \\
& =S_{N} \oplus N B \backslash T_{N-1} \oplus(N-1) B \cup S_{N-1} \oplus(N-1) B \backslash \ldots  \tag{48}\\
& \backslash T_{0} \cup S_{0}
\end{align*}
$$

where $X_{i}{ }^{\prime}, X_{i}, S_{i}$, and $T_{i}$ are defined in $(16,17),(19,20)$, (40, $41)$, and $(44,45)$.

We first show that all the approximations contain $X$ as a subimage. Following the derivation process, we first have $X$ $=X \circ B \cup S_{0}=X^{\prime} \cup S_{0}$ with $X^{\prime}=X \circ B$. We then have $X^{\prime}=$ $X^{\prime} \bullet B^{R} \backslash T_{0}=X_{1} \backslash T_{0}$ and $X=X_{1} \backslash T_{0} \cup S_{0}$ with $X_{1}=X^{\prime} \bullet B^{R}$. Now consider the approximation step $X_{1} \approx X_{1} \circ 2 B \cup S_{1} \oplus B$


Fig. 3. The skeleton points of the standard and the new skeleton transforms.
$=X_{1}{ }^{\prime} \cup S_{1} \oplus B$. Note that $X_{1}=X^{\prime} \bullet B^{R} \supseteq X^{\prime}$ and $X_{1} \circ 2 B \cup$ $S_{1} \oplus B=X_{1}{ }^{\prime} \cup S_{1} \oplus B=X_{1} \circ B$ contains all size-one disks in $X_{1}$. So $X_{1}{ }^{\prime} \cup S_{1} \oplus B$ also contains all size-one disks in $X^{\prime}$. From $X^{\prime}=X^{\prime} \bullet B^{R} \backslash T_{0}$, we can see that $T_{0}$ does not contain any points in $X^{\prime}$. Thus $X_{1}{ }^{\prime} \cup S_{1} \oplus B \backslash T_{0}$ still contains all size-one disks in $X^{\prime}$. Note also that $X^{\prime}=X \circ B$ is a union of size-one disks. Therefore, $X_{1}{ }^{\prime} \cup S_{1} \oplus B \backslash T_{0} \supseteq X^{\prime}$. Combining this with $X=X^{\prime} \cup S_{0}$, we get

$$
\begin{equation*}
X_{1}{ }^{\prime} \cup S_{1} \oplus B \backslash T_{0} \cup S_{0} \supseteq X \tag{49}
\end{equation*}
$$

Consider the next approximation step $X_{1}{ }^{\prime} \approx X_{1}{ }^{\prime} \bullet 2 B^{R} \backslash T_{1} \oplus$ $B=X_{2} \backslash T_{1} \oplus B$. Note that $X_{1}^{\prime} \bullet 2 B^{R} \backslash T_{1} \oplus B=X_{2} \backslash T_{1} \oplus B=$ $X_{1}{ }^{\prime} \bullet B^{R}$. Therefore

$$
\begin{equation*}
X_{2} \backslash T_{1} \oplus B \supseteq X_{1}^{\prime} \tag{50}
\end{equation*}
$$

Combining this with (49), we get $X_{2} \backslash T_{1} \oplus B \cup S_{1} \oplus B \backslash T_{0}$ $\cup S_{0} \supseteq X$. Move on to the next approximation step $X_{2} \approx X_{2} \circ$ $3 B \cup S_{2} \oplus 2 B=X_{2}{ }^{\prime} \cup S_{2} \oplus 2 B$. Note that $X_{2}=X_{1}{ }^{\prime} \bullet 2 B^{R} \supseteq$ $X_{1}{ }^{\prime}$ and $X_{2} \circ 3 B \cup S_{2} \oplus 2 B=X_{2}{ }^{\prime} \cup S_{2} \oplus 2 B=X_{2} \circ 2 B$ contains all size-two disks in $X_{2}$. So $X_{2}{ }^{\prime} \cup S_{2} \oplus 2 B$ also contains all size-two disks in $X_{1}{ }^{\prime}$. From $X_{2} \backslash T_{1} \oplus B \supseteq X_{1}{ }^{\prime}$ in (50), $T_{1} \oplus B$ does not contain any points in $X_{1}{ }^{\prime}$. Thus $X_{2}{ }^{\prime} \cup$ $S_{2} \oplus 2 B \backslash T_{1} \oplus B$ still contains all size-two disks in $X_{1}{ }^{\prime}$. Note also that $X_{1}{ }^{\prime}=X_{1} \circ 2 B$ is a union of size-two disks. Therefore $X_{2}{ }^{\prime} \cup S_{2} \oplus 2 B \backslash T_{1} \oplus B \supseteq X_{1}{ }^{\prime}$. Combining this with (49), we get $X_{2}{ }^{\prime} \cup S_{2} \oplus 2 B \backslash T_{1} \oplus B \cup S_{1} \oplus B \backslash T_{0} \cup S_{0}$ $\supseteq X$. Repeating similar steps, we can show that all our approximations contain $X$ as a subimage.

We now show that all our approximations are subimages of $X$. Consider the first representation step described in (15)(17). Complementing the both sides of $X=X^{\prime} \cup S_{0}$ from (15), we get $X^{C}=\left(X^{\prime}\right)^{C} \backslash S_{0}$. Complementing the both sides of (16), we have $\left(X^{\prime}\right)^{C}=X^{C} \bullet B^{R}$. We can also write $S_{0}$ in (17) as $S_{0}=X \backslash X \circ B=X \cap(X \circ B)^{C}=X^{C} \bullet B^{R} \backslash X^{C}$. So, this is a representation step for $X^{C}$ using a closing operation and a negative skeleton subset $S_{0}$. Now look at the next representation step described in (18)-(21). Complementing the both sides of (19) gives us $\left(X_{1}\right)^{C}=\left(X^{\prime}\right)^{C} \circ B$. From (20), we have $T_{0}=X^{\prime} \bullet B^{R} \backslash X^{\prime}=X^{\prime} \bullet B^{R} \cap\left(X^{\prime}\right)^{C}=\left(X^{\prime}\right)^{C} \backslash\left(X^{\prime} \bullet\right.$ $\left.B^{R}\right)^{C}=\left(X^{\prime}\right)^{C} \backslash\left(X^{\prime}\right)^{C} \circ B$. Complementing the both sides of (21), we get $X^{C}=\left(X_{1}\right)^{C} \cup T_{0} \backslash S_{0}$. Clearly, this is a
representation step for $X^{C}$ using an opening operation and a positive skeleton subset $T_{0}$. For the next approximation step described in (22)-(25), we again first complement the both sides of (23). It gives us $\left(X_{1}{ }^{\prime}\right)^{C}=\left(X_{1}\right)^{C} \bullet 2 B^{R}$. From (24), we have $S_{1}=X_{1} \ominus B \backslash X_{1} \ominus B \circ B=X_{1} \ominus B \cap\left(X_{1} \ominus B \circ B\right)^{C}=$ $\left(X_{1} \ominus B \circ B\right)^{C} \backslash\left(X_{1} \ominus B\right)^{C}=\left(X_{1}\right)^{C} \oplus B^{R} \bullet B^{R} \backslash\left(X_{1}\right)^{C} \oplus B^{R}$. Complementing the both sides of (25) gives us $X^{C} \approx\left(X_{1}{ }^{\prime}\right)^{C} \backslash$ $S_{1} \oplus B \cup T_{0} \backslash S_{0}$. This is an approximation step for $X^{C}$ using a closing operation and a negative skeleton subset $S_{1}$. Similarly, from (26)-(29), we get $\left(X_{2}\right)^{C}=\left(X_{1}{ }^{\prime}\right)^{C} \circ 2 B, T_{1}=$ $\left(X_{1}{ }^{\prime}\right)^{C} \ominus B \backslash\left(X_{1}{ }^{\prime}\right)^{C} \ominus B \circ B$, and $X^{C} \approx\left(X_{2}\right)^{C} \cup T_{1} \oplus B \backslash S_{1} \oplus B$ $\cup T_{0} \backslash S_{0}$. This is an approximation step for $X^{C}$ using an opening operation and a positive skeleton subset $T_{1}$. This process can be repeated for the remaining approximation steps. Each representation/approximation step for $X$ using an opening operation is a representation/approximation step for $X^{C}$ using a closing operation and vice versa. Even though the representation/approximation sequence for $X^{C}$ begins with a step using a closing operation, we can still use the similar techniques that we used earlier to show that all the approximations for $X^{C}$ actually contain $X^{C}$ as a subimage. That means that all the original approximations for $X$ are subimages of $X$. Combined with the earlier results that all the original approximations contain $X$ as a subimage, we conclude that all these approximations are exact representations of $X$.

## 4 Representation Examples

We now go back to the shape in Fig. 1(c). The standard skeleton transform uses 151 internal skeleton points, as shown in Fig. 3(a), to represent this shape. Our new algorithm only uses 20 internal and external skeleton points. Fig. 3(b) shows the internal skeleton points and Fig. 3(c) shows the external skeleton points of the new algorithm. In our implementation of both algorithms, we use two structuring elements $B_{0}$ and $B_{1}$ shown in Fig. 4 to define discrete disks of different sizes:

$$
\begin{gather*}
B=B_{0}  \tag{51}\\
i B=(i-1) B \oplus B_{(i-1) \bmod 2}, \text { for } i \geq 2 \tag{52}
\end{gather*}
$$

The skeleton subset formulas now become


Fig. 4. Two structuring elements: (a) $B_{0}$; (b) $B_{1}$.

$$
\begin{gather*}
S_{\mathrm{i}}=X_{i} \ominus i B \backslash X_{i} \ominus i B \circ B_{i \bmod 2}  \tag{53}\\
T_{i}=X_{i}^{\prime} \oplus i B^{R} \bullet B^{R}{ }_{i \bmod 2} \backslash X_{i}^{\prime} \oplus i B^{R} \tag{54}
\end{gather*}
$$

For the dog shape in Fig. 5(a), the highest order nonempty internal skeleton subset is $S_{15} . S_{15} \oplus 15 B$, which is shown in Fig. 5(b), is the initial approximation to $X$. To improve this approximation, additional internal and external skeleton subsets are applied to add and remove points. The partial reconstruction in Fig. 5(c) is created by applying all the skeleton subsets down to order 10. Fig. 5(d) shows the reconstruction using all the skeleton subsets down to order 5. The reconstruction using all the skeleton subsets down to order 2 is shown in Fig. 5(e). The exact reconstruction is obtained if we use all the skeleton subsets. We can see that by adding and removing smaller and smaller scale parts, more and more accurate details are being created by this process. This process is similar to the creation of a clay sculpture by a sculptor. The final sculpture is created by iteratively adding and removing clay, in gradually smaller pieces, to and from the initial rough shape. The total number of internal and external skeleton points used by the generalized skeleton transform to represent the dog shape is 407. The standard skeleton transform uses 257 internal skeleton points. For many shapes, using two types of skeleton points simultaneously will cause more skeleton points to be used. However, the main advantage of the generalized skeleton transform is that it provides a more general and more powerful framework. It also provides a more natural way of modeling the approximation and reconstruction of binary shapes.

Fig. 6 shows a fractal shape and its approximations. This shape has many internal holes of various sizes. Its external boundaries also contain many structures of different scales. Fig. 6 shows the gradual reconstruction of the original shape using more and more lower-order internal and external skeleton subsets. The smallest order skeleton subsets used in these approximations are of orders $34,20,15,10,5,2$, and 1. For this shape, the standard skeleton transform uses 2363 internal skeleton points. Our new algorithm uses 1930 internal and external skeleton points. The reconstruction process agrees well with our intuitive concept of describing a shape in a gradual process of describing main structures to fine details.

## 5 Conclusions

We have developed a generalized skeleton transform that represents a binary shape using both internal and external skeleton points. Using this representation, a shape can be approximated at different levels. The roughest approximation is obtained by applying opening and closing operations alternately to the original shape using disk structuring elements of increasing sizes. More accurate approximations can be reconstructed by alternately adding and removing disk parts of decreasing sizes from the initial approximation. The standard skeleton transform can be seen as a special case of our algorithm. In the standard skeleton transform, only opening operations are used in deriving skeleton subsets and only "addition" (set union) operations are used to rebuild more accurate approximations.

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Fig. 5. A dog shape and its reconstructions.


Fig. 6. A fractal shape and its reconstructions.

