The Weighted Euler Curve Transform for Shape and Image Analysis

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Abstract

The Euler Curve Transform (ECT) of Turner et al. is a complete invariant of an embedded simplicial complex, which is amenable to statistical analysis. We generalize the ECT to provide a similarly convenient representation for weighted simplicial complexes, objects which arise naturally, for example, in certain medical imaging applications. We leverage work of Ghrist et al. on Euler integral calculus to prove that this invariant—dubbed the Weighted Euler Curve Transform (WECT)—is also complete. We explain how to transform a segmented region of interest in a grayscale image into a weighted simplicial complex and then into a WECT representation. This WECT representation is applied to study Glioblastoma Multiforme brain tumor shape and texture data. We show that the WECT representation is effective at clustering tumors based on qualitative shape and texture features and that this clustering correlates with patient survival time.

1. Introduction

Tools from algebraic topology have become increasingly popular in shape analysis applications over the past several years. At an intuitive level, the topological perspective is appealing because algebraic topology is, at its core, designed to extract tractable algebraic invariants from complex shape data. The dominant technique in topological shape analysis is persistent homology, which summarizes multiscale topological features of a shape, where scale is measured relative to some filtration function. Roughly, for a continuous function \( f : X \to \mathbb{R} \) on a topological space \( X \) (satisfying certain tameness conditions), one computes the degree-\( k \) homology of the sublevel sets \( f^{-1}((-\infty, r]) \) and tracks “births” and “deaths” of homological features as the filtration value \( r \) is increased. This produces a summary statistic for the pair \((X, f)\) called a persistence diagram (see standard references \([19,9]\)), which can be used as a proxy for \( X \) in shape analysis applications. This approach has been taken in several shape analysis tasks, with shape data coming from cortical surfaces \([13]\), brain artery systems \([3]\), proteins \([29]\) and leaf contours \([37]\). While the persistence diagram of a pair \((X, f)\) provides a computationally tractable shape summary, the complex structure of the invariant means that it is difficult to incorporate into statistical models. A simpler invariant is the Euler curve of \((X, f)\): this is an integer-valued function on \( \mathbb{R} \) whose value at \( r \) is the Euler characteristic (i.e., the alternating sum of ranks of the homology groups) of the sublevel set \( f^{-1}((-\infty, r]) \).

Given shape data, one must answer the question of which filtration function to apply in order to apply these topological methods. For a shape represented as a simplicial complex \( K \) embedded in a Euclidean space \( \mathbb{R}^d \), recent work has advocated for using an ensemble of filtration functions given by the height function along directions sampled from the unit sphere \( S^{d-1} \). The collection of all persistence diagrams for these height filtrations is referred to as the persistent homology transform of \( K \). Likewise, the collection of Euler curves for all filtration directions is called the Euler curve transform (ECT) for \( K \). The ECT provides a particularly attractive shape representation, as its simplistic structure allows it to be easily incorporated into statistical models. This was the approach taken in \([14]\), where the ECTs for Glioblastoma Multiforme (GBM) brain tumor shapes were used as covariates in a model for survival prediction.

In this paper, we consider a variant of the ECT, which we dub the weighted Euler Characteristic Transform (WECT). This object is defined for shape data consisting of an embedded simplicial complex \( K \) endowed with an extra weighting function \( g \). The pair \((K, g)\) is referred to as a weighted simplicial complex. The WECT invariant incorporates both the shape of \( K \) and the weighting function \( g \) into a topological summary. Our motivation for defining this summary also comes from analysis of brain tumor data, which is naturally given as a segmented grayscale image. The segmented shape is used to construct a simplicial complex \( K \) embedded in \( \mathbb{R}^2 \), and the grayscale pixel values inside the shape define the weight function \( g \). While the WECT is a simple
generalization of the ECT, it is able to efficiently incorporate vital information that is ignored by the ECT.

1.1. Contributions and Organization of Paper

The proposed mathematical framework is laid out in detail in Section 2. There, we give a precise definition of the WECT as a generalization of ideas appearing in [27, 31]. We show that recent work of Ghrist, Levanger and Mai implies that the WECT is a complete descriptor of weighted simplicial complexes, i.e., two weighted simplicial complexes have the same WECT if and only if they are equal. In this section, we also provide comparisons between the WECT and other techniques appearing in the topological shape analysis literature. In Section 3, we demonstrate some applications of the WECT framework. We begin with a toy example exploring the utility of the WECT in classifying and registering MNIST digit images. Next, we explore a higher-dimensional example exploring the utility of the WECT in classifying glioblastoma multiforme tumors using WECT representations. Using a simple distance-based clustering scheme, we are able to distinguish clusters of tumors with low survival times, purely from imaging data. Open source code for producing and analyzing WECTs has been made publicly available [27].

2. Mathematical Framework

In this section, we lay out the mathematical framework for the WECT. We begin by reviewing some basic definitions in order to set notation.

2.1. Simplicial Complexes and the Euler Characteristic

Let $K$ be a simplicial complex embedded in some Euclidean space $\mathbb{R}^d$. That is, $K$ is a set of embedded simplices $\sigma$. Each $\sigma$ is the convex hull of a set of $k+1$ points in general position in $\mathbb{R}^d$, where $k \leq d$ is the dimension of the simplex; we write $k = \dim(\sigma)$. For example, a $0$-dimensional simplex is a point, a $1$-dimensional simplex is a closed line segment and a $2$-dimensional simplex is a triangle. The $k$ points defining $\sigma$ are called its vertices. The convex hull of $\ell < k$ of these vertices is also a simplex of $K$ and is called an $\ell$-dimensional face of $\sigma$. If $\tau$ is a face of $\sigma$, we write $\tau < \sigma$. If $\sigma$ and $\tau$ are simplices of $K$, we require that $\sigma \cap \tau$ is also a simplex of $K$. The maximum dimension of a simplex in $K$ is called the dimension of $K$, denoted $\dim(K)$. A collection of simplices of $K$ which itself forms a simplicial complex is called a subcomplex of $K$. The union of all simplices of $K$ of dimension less than or equal to $\ell$ is a subcomplex called the $\ell$-skeleton of $K$, denoted $K^{\leq \ell}$. The set of simplices of $K$ of dimension exactly $\ell$ is denoted $K^{\ell}$; note that $K^{\ell}$ is not a simplicial complex in general.

Abusing notation, we will alternate between treating each embedded simplicial complex as a combinatorial object (a set of simplices) and as a geometric object (a set of points in $\mathbb{R}^d$). We hope that the interpretation should always be clear from context.

A simple combinatorial invariant of a simplicial complex is its Euler characteristic, denoted $\chi(K)$. The Euler characteristic is defined as

$$\chi(K) = \sum_{d=0}^{\dim(K)} (-1)^d \cdot \# K^d,$$

where $\# A$ will generally be used to denote the cardinality of a set $A$. The concept of the Euler characteristic generalizes to more flexible classes of spaces, and it is a basic fact of algebraic topology that $\chi$ is a homotopy equivalence invariant. Simplicial complexes form a convenient category for computation, since they can be represented abstractly in a purely combinatorial way by keeping track of all simplices and their inclusions. In this paper, we are focused on the geometrically motivated case where are simplicial complexes are specified by an embedding into a Euclidean space. While not strictly necessary, the invariants we describe are most interesting when $K \subset \mathbb{R}^d$ is a $d$-dimensional simplicial complex. Moreover, we restrict our attention to the finite setting, i.e., $\# K^d$ finite for all $\ell$.

2.2. Euler Curve Transform

Consider a function $f : K \to \mathbb{R}$ as an assignment of a real number to each simplex of $K$, i.e., the function is constant along faces. The function is a filtration function if each sublevel set $f^{-1}((\infty, r])$ is a subcomplex of $K$. A filtration function induces a chain of inclusions of simplicial complexes $f^{-1}((\infty, r_1]) \subset f^{-1}((\infty, r_2]) \subset \cdots \subset f^{-1}((\infty, r_n])$, where $r_1 < r_2 < \cdots < r_n$ are the finitely many (using the assumption that $K$ is finite) values in the range of $f$. From this data, one obtains the Euler curve $\chi_f : \mathbb{R} \to \mathbb{Z}$ defined as $\chi_f(r) = \chi(f^{-1}((\infty, r]))$.

Given data consisting of an embedded simplicial complex and a relevant function (or more general space and function where similar concepts can be defined), the Eu-
ler curve produces a multiscale topological summary which is amenable to classical analysis, and can be viewed as a simplification of the richer but more computationally taxing persistence diagram [19, 9]. On the other hand, if a relevant function is not provided, one is left with the question of how to filter the simplicial complex.

It was observed in [41] that for an embedded complex \( K \subset \mathbb{R}^d \), there is a family of natural filtration functions: orthogonal projections onto the oriented one-dimensional subspaces of \( \mathbb{R}^d \), which can be parameterized by the unit sphere \( S^{d-1} \subset \mathbb{R}^d \). The Euler Curve Transform (ECT) of an embedded simplicial complex \( K \subset \mathbb{R}^d \) is the function \( \text{ECT}_K : S^{d-1} \times \mathbb{R} \to \mathbb{Z} \) defined as

\[
\text{ECT}_K(v, r) = \chi_{p_v}(r),
\]

with \( p_v : K \to \mathbb{R} \) defined on the vertex set \( K^0 \) by the dot product

\[
p_v(\sigma) = v \cdot \sigma. \tag{1}
\]

The function is extended inductively to higher-dimensional simplices as

\[
p_v(\sigma) = \max\{p_v(\tau) \mid \tau < \sigma\}. \tag{2}
\]

In practical computations, one uses an approximation of the ECT given by sampling finitely many projection directions from \( S^{d-1} \) and finitely many filtration values from \( \mathbb{R} \).

One can also apply a smoothing operator to each single variable function \( \text{ECT}_K(v, \cdot) \) to obtain the Smooth Euler Curve Transform (SECT). The SECT was applied in [14] to study Glioblastoma Multiforme tumor imaging data. In particular, the SECT served as a shape covariate in a Gaussian process regression model for survival prediction. Another variant of the ECT—very closely related to the one that we consider in subsequent sections—was applied in [4] to provide a topological signature for grayscale image data.

### 2.3. Weighted Euler Characteristic

Next, suppose that our data consists of an embedded simplicial complex \( K \subset \mathbb{R}^d \) together with a function \( g : K \to \mathbb{N} \), where \( \mathbb{N} = \{1, 2, \ldots\} \). We refer to the pair \((K, g)\) as a weighted simplicial complex. The goal is to define a variant of \( \text{ECT}_K \), which also incorporates data from \( g \). We note that weighted simplicial complexes have already appeared in the literature in various contexts. To the best of our knowledge, they were first studied in [18], where a homology theory was developed. Abstract weighted simplicial complexes, i.e., those which do not come with a preferred embedding into a Euclidean space, serve as models for collaboration networks [11] and Vietoris-Rips complexes for weighted point clouds [38]. We provide some examples of embedded weighted simplicial complexes next.

**Example 1.** Our main motivating example comes from grayscale images containing a region of interest, e.g., a tumor image with a segmentation mask, which can be converted into weighted simplicial complexes using Algorithm 4. An example of this process is described in Figure 2.

**Example 2.** Although the main examples considered in this paper will be of the form described in Example 7, we note that there are many other situations where one might wish to consider weighted simplicial complexes. Given shape data as a simplicial complex \( K \), one could consider the weight function \( g \) as an annotation or measure of importance. For example, if \( K \) is a complex representing a molecule shape, the weight function could be used to annotate different atom types. If \( K \) is an anatomical surface, \( g \) can be used to indicate regions of importance landmarked by a radiologist.

For a simplicial complex \( K \) and a function \( g : K \to \mathbb{N} \), we define the weighted Euler characteristic

\[
\chi^w(K, g) = \sum_{d=0}^{\dim(K)} (-1)^d \sum_{\sigma \in K^d} g(\sigma).
\]

**Remark 1.** If \( g(\sigma) = 1 \) for all \( \sigma \in K \), then \( \chi^w(K, g) = \chi(K) \). The weighted Euler characteristic is therefore a direct generalization of the classical version.

**Remark 2.** The same definition essentially appears in [34]; the only difference is that only simplicial complexes which are finite axis-aligned lattices were considered there.

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Figure 2. Glioblastoma multiforme tumor image data. From left to right: axial slice with largest tumor area selected from a 3D MRI image; binary tumor segmentation mask; segmented tumor image; weighted simplicial complex created from the segmented tumor image. Observe that the tumor shape data from the segmentation mask is enriched by the overlaid pixel value function extracted from the original image: the level sets of the pixel value function have interesting shape and topological features.
true. In what follows, for a logical statement $S$, let $1_S$ denote the indicator function taking the value 1 if $S$ is true, and 0 if $S$ is false. Then,
\[
\sum_{z \in \mathbb{N}} \chi(g^{-1}([z, \infty))) = \sum_{d=0}^{\dim(K)} \sum_{z \in \mathbb{N}} (-1)^d \# \{ \sigma \in K | g(\sigma) \geq z \}^d
\]
\[
= \sum_{d=0}^{\dim(K)} (-1)^d \sum_{z \in \mathbb{N}} \sum_{\sigma \in K^d} 1_{g(\sigma) \geq z}
\]
\[
= \sum_{d=0}^{\dim(K)} (-1)^d \sum_{\sigma \in K^d} g(\sigma) = \chi^w(K, g).
\]

2.4. Weighted Euler Curve Transform

We now define the Weighted Euler Curve Transform (WECT) as a straightforward generalization of the ECT; the WECT is specifically designed to treat weighted simplicial complexes. Let $(K, g)$ be a weighted simplicial complex, and let $f : K \to \mathbb{R}$ be a filtration function. The weighted Euler curve associated to $f$ is the function $\chi^w_f : \mathbb{R} \to \mathbb{Z}$ defined as
\[
\chi^w_f(r) = \chi^w(f^{-1}((-\infty, r]), g),
\]
where $g$ is understood by context to be the restriction of $g$ to the subcomplex $f^{-1}((-\infty, r])$. We then define the WECT of a weighted simplicial complex $(K, g)$ with $K \subset \mathbb{R}^d$ as the function $\text{WECT}_{K, g} : S^{d-1} \times \mathbb{R} \to \mathbb{Z}$ defined as
\[
\text{WECT}_{K, g}(v, r) = \chi^w_{p_v}(r),
\]
with $p_v$ the projection function as defined in Equations (1) and (2). Clearly, if the weight function $g$ is constant and equal to one, then $\text{WECT}_{K, g} = \text{ECT}_K$.

As in the case of the ECT, a WECT is represented in practice by sampling a finite number of directions on the sphere $S^{d-1}$. An example of a WECT is shown in Figure 6. As in [14], when analyzing WECTs, we often preprocess them to improve robustness, by applying a smoothing operator. Unlike [14], we do not specify a particular smoothing operation, and leave the particular method as a hyperparameter in the data analysis pipeline.

2.5. Distance Between WECTs

The WECT of a weighted simplicial complex $(K, g)$ in $\mathbb{R}^d$ is naturally viewed as a family of integer-valued functions $\text{WECT}_{K, g}(v, \cdot) : \mathbb{R} \to \mathbb{Z}$, parameterized by $S^{d-1}$.
2.6. Injectivity of the WECT

Inverse problems in topological data analysis have recently become an active topic of research [36]. The basic general question is: Is it possible for inequivalent spaces to be mapped to the same topological summary statistic? This question has recently been tackled for various flavors of topological signatures [22, 33, 15, 12] including Persistent Homology and Euler Curve Transforms [41, 24, 20, 17, 4, 14, 21].

The original paper on the ECT [41] demonstrated a uniqueness result for ECT representations of compact embedded simplicial complexes with an algorithmic proof. This perspective has been pushed further to provide a sufficient number of direction samples to guarantee injectivity [17]. It is shown in [4] that for weighted cubical complexes defined on a regular axis-aligned lattice in \( \mathbb{R}^d \), only \( 2^d \) generic samples are sufficient and an explicit reconstruction algorithm is provided. Our Algorithm [1] produces a simplicial complexes which is essentially equivalent to the cubical complexes of [4], so the reconstruction results their can be ported over directly to weighted simplicial complexes constructed via Algorithm [1].

In anticipation of the possibility of studying non-axis-aligned weighted simplicial complexes through the WECT signature, one might hope for a more general injectivity result. An alternative approach to the injectivity question for ECTs is given in [24, 17]. In these articles, the theory of Euler integral calculus is employed to prove injectivity. This approach is more theoretical and comes with the cost of a less explicit inversion algorithm. This is balanced by more general applicability. In particular, one has the following, quite general, result.

**Theorem 1** (Theorem 1. [24]). The map

\[
\mathcal{R} : \text{CF}_c(\mathbb{R}^d) \to \text{CF}(S^{d-1} \times \mathbb{R})
\]

defined by

\[
(\mathcal{R}(g)) (v, r) = \int_{\mathbb{R}^d} g(x) \cdot I_{x \cdot v \leq r} \ d\chi(x) \tag{5}
\]

is injective.

We use \( \text{CF}(\mathbb{R}^d) \) to denote the space of constructible functions; these are functions \( \mathbb{R}^d \to \mathbb{Z} \) whose level sets satisfy a certain tameness condition, defined Nowadays in the technical language of o-minimal set theory [2] [16, 24]. The set \( \text{CF}(S^{d-1} \times \mathbb{R}) \) is defined similarly. We are restricting to compactly supported constructible functions \( \text{CF}_c(\mathbb{R}^d) \). This space in particular contains admissible functions defined on embedded simplicial complexes in \( \mathbb{R}^d \). The right
side of Equation (5) is defined in terms of Euler integration. Roughly, one treats the Euler characteristic formally as a measure, allowing for integration of sufficiently well-behaved functions. The transform $\mathcal{R}$ can be understood as a topological version of the classical Radon transform used in tomography applications [25]. Theorem [1] is proved by appealing to a general result of Schapira on inverting topological Radon transforms of this type [20]. The authors of [24] observe that if $g$ is the indicator function for an embedded simplicial complex $K$, then $\mathcal{R}(g)$ is exactly the ECT for $K$, whence the ECT is injective [24 Corollary 1]. On the other hand, if we consider functions $g$ which are admissible weight functions on embedded simplicial complexes, we obtain the following result as an immediate corollary.

**Theorem 2.** The Weighted Euler Characteristic Transform is injective on the space of weighted simplicial complexes. That is, if $(K_1, g_1)$ and $(K_2, g_2)$ are weighted simplicial complexes in $\mathbb{R}^d$ with $\text{WECT}_{K_1, g_1} = \text{WECT}_{K_2, g_2}$, then $(K_1, g_1) = (K_2, g_2)$.

### 2.7. Comparison to Other Methods

The WECT provides a topological signature which simultaneously incorporates shape data and non-geometric weight data. In the case of image data, by discretely sampling the domain $S^{d-1} \times \mathbb{R}$ one obtains a discrete signature with a similar memory footprint to the original image. However, we show experimentally that the WECT provides a representation, which is more effective at distinguishing shape features. In this subsection, we compare the WECT representation to other shape descriptors appearing in the topological data analysis literature.

**Persistent Homology.** The WECT representation has several benefits over the commonly used persistent diagram signature. Foremost, it is a nontrivial task to simultaneously incorporate geometric and non-geometric features into a persistence diagram. One approach is to use a multiparameter filtration of the dataset [25][10]. The major drawback of such an approach is that multiparameter persistent homology does not in general admit a convenient analogue of the persistence diagram statistics used in classical persistent homology. An alternative approach to incorporating geometric and non-geometric features into persistent cohomology was recently proposed in [8], where an enriched barcode representation is obtained through least squares optimization of persistent cohomology cycle representatives.

The simple WECT representation for weighted simplicial complex data also has the benefit of immediately providing a vectorized topological signature. This allows straightforward usage of WECT summaries as covariates in statistical models—this was the main idea of [14], where the ECT summaries were used as covariates in a Gaussian process regression for prediction of survival times of subjects with Glioblastoma Multiforme brain tumors. This is in stark contrast to analysis using persistence diagrams or barcodes from persistent homology. Indeed, a persistence diagram is an unstructured point cloud in $\mathbb{R}^2$ and care must be taken to vectorize this signature in order to incorporate it into statistical models. There are several extant vectorization methods in the literature, including persistence landscapes [6] and persistence images [1], as well as more straightforward feature aggregation [5]. Any vectorization of the persistence diagram space necessarily distorts its natural latent geometry, since the canonical metric on persistence diagrams, the bottleneck distance, is non-Euclidean [7].

**Variants of the ECT.** When studying simplicial complexes arising from grayscale image data, one could imagine other relevant simplicial complexes to which one could apply the standard ECT. Examples include thresholding pixel values in the image and building restricted two-dimensional complexes or using the pixel values to build a three-dimensional simplicial complex. We found these approaches to give unsatisfactory performance on our tumor dataset, although they may be viable approaches for other applications.

### 3. Applications

#### 3.1. Classification of MNIST Digit Images

To understand the descriptive power of the WECT representation of image data, we first explore its ability to classify images from the ubiquitous MNIST handwritten digit dataset [30]. We use a small subset of 1000 $28 \times 28$ grayscale images, evenly distributed over 10 digits $0, 1, \ldots, 9$. As a baseline, we treat each image as a vector in $\mathbb{R}^{28 \times 28}$ and classify them using Support Vector Machines (SVM) with a linear kernel. Next, we produce WECT representations of all digit images. In this experiment, we discretize $S^1 \times \mathbb{R}$ into a $25 \times 50$ grid (i.e., $25$ Euler curve directions, $50$ points along each curve domain). We also smooth the Euler curves to improve robustness using a Gaussian kernel with window size $0.2 \cdot 50$ (these particular parameters were chosen in a tuning step, but we found that the results are generally insensitive to the parameter choice). We then considered each WECT representation as a vector in $\mathbb{R}^{25 \times 50}$ and classified using SVM with a linear kernel. We also produced smoothed ECT representations with similar parameters and ran an SVM classification. The ten-fold cross-validated classification rates from these experiments are displayed in Table [1].

The classification results show that the WECT representation of the digit images is adept at encoding and distinguishing shape features, while having a similar memory footprint to the original image representation. It also outperforms the classification using smoothed ECT representations. We stress that this classification result is, of course, not meant to be competitive with those obtained by deep learning methods. Rather, this simple experiment suggests
Table 1. SVM ten-fold classification performance of vectorized image, ECT and WECT representations for the MNIST digit data.

| Representation      | Classification Rate |
|---------------------|---------------------|
| Image $\mathbb{R}^{28 \times 28}$ | 87.84 ± 1.42 % |
| ECT $\mathbb{R}^{25 \times 50}$ | 89.88 ± 1.66 % |
| WECT $\mathbb{R}^{26 \times 50}$ | 94.68 ± 1.57 % |

that the WECT representation produces an interesting shape summary for this type of image data, which is computationally efficient and can be trivially incorporated into various statistical models.

To get a more detailed qualitative picture of the differences between the raw image, ECT and WECT representations of the MNIST image data, we also computed t-SNE embeddings [31] for each representation; see Figure 4. While class separation is apparent in all three embeddings, it is immediately evident that the embeddings of the ECTs and WECTs are much more distinctly clustered. On the other hand, one can easily see how classification errors arise in the ECT embedding. We believe that these errors occur because the ECT is more sensitive to topological differences between digits, while the WECT smooths these differences using weight data.

3.2. Rigid and Scale Registration

One benefit of the simplicial complex representation of image data is that registering over scale and rigid transformations (translations and rotations) becomes trivial. Once a pair of images have been converted to weighted simplicial complexes $(K_1, g_1)$ and $(K_2, g_2)$, they can be immediately registered with respect to translation and scaling by centering each complex at the origin, and normalizing (treat-
Table 2. Clusterwise mean and median survival.

|        | Mean | 12.9 | 20.2 |
|--------|------|------|------|
|        | Med. | 9.6  | 15.2 |

Figure 6. Weighted simplicial complex representations of tumors from the low survival time cluster in Table 2.

Table 3. Clusterwise mean and median survival for Figure 7.

|       | Blue | Cyan | Red  | Magenta | Yellow | Green |
|-------|------|------|------|---------|--------|-------|
| Mean  | 18.1 | 28.0 | 17.9 | 19.4    | 5.0    | 12.6  |
| Med.  | 14.9 | 22.3 | 14.3 | 20.4    | 4.5    | 10.7  |

the domain of the Euler curve for each direction. The Euler curves were smoothed using a Gaussian kernel with a smoothing window of ten. Next, the $L^2$ distance between each pair of smoothed WECT representations was computed with registration of the tumor images over rotations (see Section 3.2). We applied hierarchical clustering with Ward linkage to the $63 \times 63$ distance matrix, which first suggested three natural clusters. The clusterwise mean and median survival times (in months) are reported in Table 2.

These statistics suggest that the clusters are roughly characterized as low, medium and high survival. Figure 6 shows tumors from the low survival cluster; they are visually irregular in shape and intensity distribution, which explains their presence as a distinct cluster. To explore the data in more depth, we consider the clustering dendrogram with this cluster of tumors removed. Figure 7 shows this dendrogram on the remaining 58 tumors, with six highlighted clusters; mean and median survival times for patients in these clusters are shown in Table 3. Inspecting the tumors in these clusters, one can observe various common qualitative shape and intensity features. For example, the tumors in the blue and cyan clusters both tend to have intensity patterns with a ring-like structure near the boundary. The tumors in the blue cluster tend to have higher irregularity in shape and/or intensity patterns, see Figure 8.

4. Future Work

Our work suggests several directions for future research. Driven by the qualitative distance-based clustering results presented here, we next plan to incorporate WECT representations into more sophisticated statistical models for tumor survival prediction. The WECT representation is flexible in the sense that it provides a summary of any weighted simplicial complex. We plan to apply this type of analysis to other shape data, such as weighted simplicial complexes representing annotated molecule shapes. On the theoretical side, there are several interesting questions left open. Principally, one could attempt to strengthen Theorem 2 on injectivity of the WECT in several ways. In its current form, it is mainly a theoretical result and an implementation of an inversion algorithm would be desirable. A practical version of such a construction would only require information about weighted Euler curve measurements in finitely many directions, along the lines of results in [17] on the ECT. It would also be interesting to have a quantitative version of the injectivity theorem; if WECTs of $(K_1, g_1)$ and $(K_2, g_2)$ are close in $L^2$ distance, does this imply that $(K_1, g_1)$ and $(K_2, g_2)$ are close in some resonable metric, such as Wasserstein distance (treating a normalization of $g_j$ as a probability measure supported on $K_j$)?

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