Distances and Statistics of Local Molecular Clouds in the First Galactic Quadrant

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Abstract
We present an analysis of local molecular clouds (−6 < V_LSR < 30 km s^{-1}, i.e., <1.5 kpc) in the first Galactic quadrant (257° < l < 49°7 and |b| < 5°), a pilot region of the Milky Way Imaging Scroll Painting (MWISP) CO survey. Using the Spectral Clustering for Interstellar Molecular Emission Segmentation algorithm to divide large molecular clouds into moderate-size ones, we determined distances to 28 molecular clouds with the background-eliminated extinction-parallax method using the Gaia DR2 parallax measurements aided by A_F and A_V; the distance ranges from 250 to about 1.5 kpc. These incomplete distance samples indicate a linear relationship between the distance and the radial velocity (V_LSR) with a scatter of 0.16 kpc, and kinematic distances may be systematically larger for local molecular clouds. In order to investigate fundamental properties of molecular clouds, such as the total sample number, the line width, the brightness temperature, the physical area, and the mass, we decompose the spectral cube using the density-based spatial clustering of applications with noise (DBSCAN) algorithm. Post-selection criteria are imposed on DBSCAN clusters to remove the noise contamination, and we found that the separation of molecular cloud individuals is reliable based on a definition of independent consecutive structures in l–b–V space. The completeness of the local molecular cloud flux collected by the MWISP CO survey is about 80%. The physical area, A, shows a power-law distribution, dN/dA ∝ A^{-2.20±0.18}, while the molecular cloud mass also follows a power-law distribution but is slightly flatter, dN/dM ∝ M^{-1.96±0.11}.

Unified Astronomy Thesaurus concepts: Molecular clouds (1072); Interstellar clouds (834); Astrostatistics (1882); Interstellar dust extinction (837); Interstellar molecules (849)

1. Introduction
Molecular clouds, the molecular phase of the interstellar medium (ISM), are fundamental components of the Milky Way (Swings & Rosenfeld 1937; Weinreb et al. 1963; Carruthers 1970; Heger & Dame 2015). The sizes and masses of molecular clouds range over several orders of magnitudes (Motte et al. 2018), from small diffuse molecular clouds (e.g., those at high Galactic latitudes with sizes and masses of 0.1 pc and 0.1 M☉, respectively; Magnani et al. 1996) to giant molecular clouds (40 pc and 10⁷ M☉; Solomon et al. 1979; Solomon & Sanders 1980). The radial velocity dispersion (the Gaussian standard deviation of the spectral profile) of molecular clouds is about 1–10 km s^{-1} (Wilson et al. 1970; Larson 1981; Riener et al. 2019). Although molecular clouds are involved in a number of physical processes occurring in the Milky Way, such as star formation (e.g., McKee & Ostriker 2007; Kennicutt & Evans 2012) and large-scale Galactic structure development (e.g., Dame et al. 1986; Roman-Duval et al. 2010), many key mechanisms of molecular clouds are still unclear, for instance, their formation and evolution (see Dobbs et al. 2014, for a review).

Large-scale CO surveys, with high spatial dynamic ranges, are essential to understanding molecular clouds. Because CO is much easier to excite than H2 in low-temperature environments (Goldreich & Kwan 1974; Heger et al. 1998; Bolatto et al. 2013), it is frequently used as a proxy of H2 to study the dynamical (e.g., Snell et al. 1984; Zhang et al. 2005; Li et al. 2019), physical (e.g., Solomon et al. 1971; Miville-Deschênes et al. 2017; Colombo et al. 2019; Grudić & Hopkins 2019), and chemical (e.g., van Dishoeck & Black 1988; Visser et al. 2009; Wang et al. 2019) properties of molecular clouds. Modern CO surveys are now characterized by large sky coverages, high sensitivities, high spatial and velocity resolutions, and multiple transition and isotopolog lines. Heyer & Dame (2015) provide a summary (see Figure 2 therein) of large-scale CO surveys conducted with single-dish telescopes until 2015, and significant progress has been made afterward. To date, the CfA–U.Chile CO survey (Dame et al. 2001) has the largest sky coverage (0° < l < 360°) with an angular resolution of 8′5, and a radial velocity resolution of about 0.65 km s^{-1}. The spectrum noise is about 0.25 K, which changes slightly from region to region due to different observation strategies. A new CO survey toward the northern sky (−10° < l < 250° and |b| < 5°), the Milky Way Imaging Scroll Painting (MWISP) survey (Su et al. 2019), records three CO isotopolog lines, 12CO (J = 1 → 0), 13CO (J = 1 → 0), and C18O (J = 1 → 0), with angular and velocity resolutions of ~50′′ and ~0.2 km s^{-1}, respectively, and an approximate 12CO noise rms of 0.5 K (~0.3 K for 13CO and C18O). The FOREST unbiased Galactic plane imaging survey with the Nobeyama 45 m telescope project (Umemoto et al. 2017) also observes three CO isotopolog lines with a finer angular resolution (20′′) but is less sensitive (1.47 K at a velocity resolution of 1.3 km s^{-1}). As for other CO transition lines, the 15 m James Clerk Maxwell Telescope (JCMT) has performed two surveys in the first Galactic quadrant: the JCMT 12CO (J = 3 → 2) High-Resolution Survey of the Galactic plane (COHRS; Dempsey et al. 2013) and the 13CO/C18O (J = 3 → 2) Heterodyne Inner Milky Way Plane Survey (CHIMPS; Rigby et al. 2016), with angular resolutions of 14″ and 15″, respectively. Another recent CO survey, covering 13CO (J = 2 → 1) and C18O (J = 2 → 1) with the Atacama Pathfinder Experiment, is the structure, excitation, and dynamics of the inner Galactic ISM survey (−60° ≤ l ≤ 18°; Schuller et al. 2017).

With the progress of CO surveys, high-dynamic-range statistical analyses of molecular clouds are now achievable.
Usually this is done by decomposing large data cubes into small components with appropriate algorithms, such as dendrograms (Rosolowsky et al. 2008), the Spectral Clustering for Interstellar Molecular Emission Segmentation (SCIMES; Colombo et al. 2015), FellWalker (Rigby et al. 2019), and GaussPy+ (Riener et al. 2019). The definition of molecular clouds, however, is not consistent across different algorithms, and the choice of algorithm hinges on the desired molecular cloud properties and specific research goals. For example, GaussPy+ is useful in dynamical analysis of molecular clouds (Riener et al. 2020), and the dendrogram and SCIMES are more appropriate in splitting large consecutive structures in position–position–velocity (PPV) space into moderate-size structures (Colombo et al. 2019).

Previous studies have provided many insights into the molecular cloud properties, and in this work, we investigate molecular clouds from another point of view. The region we analyzed is the local molecular clouds in the first Galactic quadrant \((25^\circ < l < 49^\circ, |b| < 5^\circ, ~ \text{and} ~ -6 < V_{LSR} < 30 ~ \text{km s}^{-1}\) using the CO spectra obtained with the MWISP CO survey. Su et al. (2019) provided an overview of the MWISP project and molecular clouds in this region in a much wider velocity range \((-80 < V_{LSR} < 130 ~ \text{km s}^{-1}\), but we only focus on the local components, which are better resolved. The main component of the local molecular clouds in this region is known as the Aquila Rift, or Serpens-Aquila Rift (e.g., Dame et al. 2001; Gutermuth et al. 2008; Bontemps et al. 2010; Su et al. 2020). We use density-based spatial clustering of applications with noise (DBSCAN; Ester et al. 1996) to extract local molecular cloud samples and examine their statistical properties.

In addition, we use the background-eliminated extinction-parallax (BEEP) method (Yan et al. 2019a) to estimate distances to molecular clouds using the Gaia DR2 catalog (Gaia Collaboration et al. 2016, 2018) supplemented by Av estimates (Anders et al. 2019). The BEEP approach was proposed to measure distances to molecular clouds in the Galactic plane where dust environments are complicated. Briefly, the BEEP method removes unrelated extinction by calibrating the stellar extinction toward molecular clouds with the extinction of stars around them, which efficiently reveals the extinction jump position caused by molecular clouds, thus deriving their distances. In the first Galactic quadrant, the dust environment is much more complicated than that in the outer Galaxy (Yan et al. 2019a), and additional treatments are needed.

We begin the next section (Section 2) with a description of the CO data, cloud identification methods, and distance calculations. Section 3 describes the distance and statistical results. Discussions on the results are presented in Section 4, and we summarize the conclusions in Section 5.

2. Data And Methods

2.1. CO Data

The first Galactic quadrant \((25^\circ < l < 49^\circ, |b| < 5^\circ, ~ \text{and} ~ -80 < V_{LSR} < 130 ~ \text{km s}^{-1}\) is a pilot region of the MWISP\(^1\) CO survey. The MWISP CO survey covers three CO isotopolog lines, but we only use \(^{12}\)CO \((J = 1 \rightarrow 0)\) to study the statistical properties of local components \((-6 < V_{LSR} < 30 ~ \text{km s}^{-1}\). The reason is that \(^{12}\)CO has the lowest critical density and the highest signal-to-noise ratio and produces the most complete molecular cloud catalog. Su et al. (2019) have provided a thorough introduction about the MWISP project and an overview of this pilot region, and here we only briefly describe the quality of the data.

Observations were obtained with the Purple Mountain Observatory (PMO) 13.7 m millimeter telescope, and the beam HPBW (half-power beam width) is \(~50^\prime\) for \(^{12}\)CO. The sky region was divided into \(30^\prime \times 30^\prime\) tiles, observations of which were merged into a mosaic of the entire CO map. The pixel size of the data cube is \(30^\prime \times 30^\prime\), and the velocity channels were regridded to 0.2 km s\(^{-1}\), The typical noise rms \((\sigma)\) of the \(^{12}\)CO line is \(~0.5\) K (see Figure 3 of Su et al. 2019), which changes slightly from tile to tile.

Figure 1 shows the integrated intensity map (a) and the \(I-V\) diagram (b) of the entire region. The radial velocity range of the Local arm is about \([-6, 25]\) km s\(^{-1}\), and to make the sample complete, we extended the velocity range to \([-6, 30]\) km s\(^{-1}\), which is the integration range of the intensity map. In order to make the noise evident, we used a white-color background, and the stripes trace the scan direction. In the \(I-V\) diagram, the noise was masked with DBSCAN (connectivity 1 and MinPts 4) down to the 1 K (\(2\sigma\)) emission level, and noise clusters are removed with the post-selection criteria. Explanations of DBSCAN and the meaning of its parameters are presented in Section 2.2.

2.2. Cloud Detection

In this study, we examine molecular clouds in general and ignore their hierarchical details, i.e., molecular clouds are defined as consecutive structures in PPV space. Statistical results are based on the properties of those independent PPV structures. With this definition, we use DBSCAN\(^2\) to identify clusters as molecular clouds. Trunks of the dendrogram\(^3\) also satisfy these requirements, but if only trunks were concerned, the dendrogram would be a special case of DBSCAN. Consequently, we do not use the dendrogram, but explore DBSCAN parameters and demonstrate the variation of the statistical results.

In addition to DBSCAN, we also use SCIMES\(^4\) to decompose large molecular clouds, but statistics with SCIMES are only used for comparison. Hierarchical density-based spatial clustering of applications with noise (HDBSCAN), an improved version of DBSCAN, is also able to identify clusters, and as discussed in Section 4.1, HDBSCAN does not provide a uniform molecular cloud definition in PPV space. Therefore, we did not use HDBSCAN.

Two parameters of DBSCAN, \(\epsilon\) and MinPts, define the connection property of voxels in PPV space. The number of points in an \(\epsilon\) radius is assigned as the density, and a minimum density of MinPts is required to be considered as core points. Directly connected (within an \(\epsilon\) radius) core points form clusters, and neighbors (within an \(\epsilon\) radius) of those core points are also considered as their cluster members. Figure 2 shows three types of connectivity in PPV space, i.e., definitions of neighborhood. Connectivity 1 corresponds to \(\epsilon = 1\) in Euclidean distance (6 neighboring points at most), \(\epsilon = \sqrt{2}\) (18 points) for connectivity 2, and \(\epsilon = \sqrt{3}\) (26 points) for

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\(^1\) http://www.radioast.nsdic.cn/mwisp.php

\(^2\) https://scikit-learn.org/stable/modules/generated/sklearn.cluster.DBSCAN.html

\(^3\) https://dendrograms.readthedocs.io/en/stable

\(^4\) https://scimes.readthedocs.io/en/latest
If only trunks were considered, the dendrogram would correspond to DBSCAN with \( \epsilon = 1 \) and MinPts = 3. We examined all three types of connectivity, and the choice of the minimum MinPts for each connectivity type is demonstrated in Section 2.4. A Python implementation of DBSCAN cloud identification is publicly available on github.\(^5\)

We examine the effects of CO emission cutoffs on statistical results. The cutoff ranges from \( 2\sigma \) (1 K) to \( 7\sigma \) with a step of \( 0.5\sigma \), and before running DBSCAN, all voxels below cutoffs are removed.

The definition of molecular clouds in SCIMES is not straightforward, due to its multistage procedure and uncertain mathematical properties. SCIMES extracts clusters from the dendrogram results, and the dendrogram is a single-linkage

\(^5\) https://github.com/SHAoqzyan/MWISPdbscan
Figure 3. SCIMES results with different criteria. The CO cutoff is 1.5 K ($3\sigma$), min_npix = 16, and min_delta = 1.5 K. See Equation (1) for the meaning of $\sigma_s$.

hierarchical clustering algorithm, which produces tree structures according to the intensities and Euclidean distances of voxel indices. Consequently, the SCIMES results are only used for a comparison purpose in statistical analyses, but SCIMES is able to split large dendrogram trunks into medium-size branches, which is useful in distance examinations. The dendrogram builds tree structures from the highest intensities (leaves) down to the cutoff value (roots), and in the tree structure, branches are structures that contain leaves or branches. The dendrogram has three parameters, min_value, min_delta, and min_npix. Min_value is a cutoff threshold of the intensity, i.e., all voxels below min_value are discarded. Min_npix is the minimum number of voxels that a cloud has to have, and min_delta is the minimum difference between the peak and the background. The background is defined as the value where leaves merge into parent branches. For isolated leaves, the background is min_value, so their minimum peak values are (min_value+min_delta). To see the effect of parameters, we fixed min_delta ($3\sigma$) and min_npix (16), and changed min_value (from $2\sigma$ to $7\sigma$ with a step of 0.5$\sigma$), examining 11 cases in total. SCIMES takes the dendrogram tree structure as a fully connected graph (in a single trunk) and splits large trunks based on the magnitude of their volume and luminosity, or other self-defined criteria (Colombo et al. 2015).

In SCIMES, we saved all structures, including isolated and unclustered leaves or branches.

We found that the default volume and luminosity criteria did not work well in the Aquila Rift region, so we used the radial velocity range as the criterion to split large trunks with SCIMES. The reason is that far molecular clouds usually have small volume and low luminosity compared with local molecular clouds, and far molecular clouds would be treated as small molecular clouds if a constant volume and luminosity criteria were used. The radial velocity, however, is independent of the distance. The second moment of radial velocities overwhelms many weak branches, so we adopted instead the minimum velocity range that contains all leaves in a branch as a proxy of its velocity dispersion. For isolated leaves, the second moment of the radial velocity is still used. The velocity dispersion is rescaled with $\sigma_s$, because SCIMES results are only used for comparison, and the choice of $\sigma_s$ is unimportant as long as large trunks are able to be decomposed. The rescaled radial velocity range is

$$s_{ij} = \exp\left(-\frac{v_{ij}^2}{\sigma_s^2}\right),$$

(1)

where $v_{ij}$ is the radial velocity range of the smallest branch that contains both the $i$th and $j$th structures, which is symmetric.

In Figure 3, we compare SCIMES results with different splitting criteria. Unlike the radial velocity range, the default volume and luminosity criteria kept a large portion of the largest dendrogram trunks in a whole piece. Because it is difficult to determine which criteria are the best and the SCIMES results are only used to see how the statistical results vary if large dendrogram trunks were decomposed, we simply used a moderate value of 20 km s$^{-1}$. The choice of criteria is rather subjective, and this is one of the reasons why SCIMES results are only used for comparison.

2.3 Post-selection Criteria

Clusters identified by DBSCAN may contain noises, so we apply post-selection criteria on raw clusters based on the voxel number, the peak brightness temperature, the area projection, and the velocity projection. The first two criteria are related to sensitivity, while the second two are related to resolution. In total, the post-selection criteria contain four conditions: (1) the minimum voxel number is 16; (2) peak intensity $\geqslant$ (min_value + $3\sigma$); (4) the projection area contains a beam, i.e., a compact $2 \times 2$ region; (4) velocity channel numbers $\geqslant 3$. We examined all criteria and used them in combination, and these criteria also apply to SCIMES clusters.

Figure 4 describes the effect of the sensitivity and resolution criteria separately. The histogram shows that most clusters
selected by sensitivity satisfy the resolution criteria, indicating that the sensitivity criteria is more strict. In practice, we used both criteria in combination, but the sensitivity criteria dominate post-selection.

2.4. Choice of MinPts

Small values of MinPts include many noises, even after applying the post-selection criteria, and we use negative brightness temperatures in spectra to demonstrate the choice of the minimum MinPts. Obviously, negative values are all noises, and after selecting using the post-selection criteria, no DBSCAN clusters should remain.

We invert the sign of the spectra and impose a 1 K \((2\sigma)\) cutoff. All possible cases of DBSCAN were examined based on this data set, and the number of remaining clusters after applying the post-selection criteria is shown in Figure 5. The minimum MinPts values that result in 0 clusters for connectivities 1, 2, and 3 are 4, 8, and 11, respectively, and reasonably, a larger \(\epsilon\) requires a higher MinPts.

2.5. Distances

We examined distances to large molecular clouds with the BEEP method proposed by Yan et al. (2019a). The BEEP method removes irregular variations of stellar extinction that are unrelated to molecular clouds and thus reveals the extinction jump point caused by targeted molecular clouds.

We used parallaxes and \(A_V\) in the Gaia DR2 catalog, supplemented by \(A_V\) (Anders et al. 2019) when \(A_V\) stars were insufficient. Anders et al. (2019) calibrated systematic errors (see Table 1 therein) of Gaia DR2 data, and in order to make the results consistent, we performed the same calibration. As suggested by Anders et al. (2019), we require all flags of the \(A_V\) values to be 0, i.e., those data are reliable. Other procedures of the Gaia DR2 data reductions follow Yan et al. (2019a).

Because distance calculations favor moderate-size molecular clouds, we used the dendrogram and SCIMES to decompose the data cube. The area of molecular clouds needs to be adequate to include sufficient on-cloud stars, and the flux needs to be large enough to cause detectable extinction. In the approximate 239 deg\(^2\) area and within 1 kpc, the total number of stars that have both good parallaxes (relative error \(<0.2\) and \(A_V\) values (all flags are 0) is 320,787, and the number of stars per unit area is about 1342. To get a 10% distance precision at 500 pc, we require that there be at least 1 star every 50 pc, so the total number of on-cloud stars within 1 kpc should be at least 20, corresponding to an area of 0.015 deg\(^2\) (216 pixels). Considering that on-cloud stars need to be located in regions

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**Figure 4.** Post-selection criteria: select by (a) minimum voxel numbers and peak intensities and by (b) minimum area and velocity projection. Raw samples are produced by DBSCAN with the 1.5 K \((3\sigma)\) cutoff, connectivity 1, and MinPts 4. A beam means a compact \(2 \times 2\) region.

**Figure 5.** Cluster numbers detected with negative CO brightness temperatures.
that show significant CO emission, a value of 1000 for min_npix (min_value = 3σ and min_delta = 3σ) is small enough to generate a complete catalog for distance measurements. With these parameter settings, we run the dendrogram, and the criteria used in SCIMES is the velocity range (see Section 2.2, σ_r = 20 km s^{-1}) instead of the volume and luminosity criteria. In total, SCIMES found 912 clusters, including unclustered structures.

SCIMES only selects substructures from large trunks and misses weak emission in the envelopes of molecular clouds. The reason is that the dendrogram uses high contour levels to distinguish substructures, and emission with lower contour levels is discarded if large trunks were replaced with their branches. To add back the weak emission, we use the dilation function in the Python skimage package to expand labeled SCIMES clusters to 2σ. By default, dilation extends large regions and shrinks small regions, so we restricted dilation only to expand into unlabeled regions. An example of one dilation step is shown in Figure 6, and after the dilation, unassigned 2σ cutoff regions are assigned the largest neighboring (connectivity 1) labels. This type of dilation prefers large label numbers near cluster boundaries, and because it is hard to determine which clusters those edge voxels should belong to, we simply follow this rule of dilation. Because dilation ignores CO values and to make sure molecular clouds split at valleys, we expanded labeled regions gradually by decreasing contour levels from 10σ to 2σ with a step of 1σ. At each step, the dilation runs recursively until all unlabeled voxels above the targeted contour level are assigned to adjacent SCIMES clusters. The dilation process is similar to expanding mountain peaks to mountain roots, and mountains are separated at valleys.

Compared with molecular clouds in the outer Galaxy (Yan et al., 2019a), the choice of on- and off-cloud regions in the first Galactic quadrant is slightly different, and stars that are affected by foreground clouds were removed. Given the complexity of molecular cloud environments, on- and off-cloud regions should be neither too large nor too small. Large regions contain contamination from other molecular clouds, making the baseline unreliable, while small regions contain insufficient stars, unable to yield robust statistical results. Consequently, we extended the region box (along l and b) that contains molecular clouds by 0.5. If a molecular cloud is both large and connected with many adjacent ones, we manually chose an on-cloud region where the cloud has sharp boundaries. If a molecular cloud does not have enough on-cloud stars and is likely to be associated with adjacent emissions, we extended the on-cloud region to include more on-cloud stars.

We removed those stars (both on- and off-cloud stars) that are affected by foreground clouds. The foreground emission of a molecular cloud is defined by means of its weighted (by the brightness temperature) mean (V_{center}) and weighted standard deviation (ΔV) of the radial velocity. Integrated intensity from −6 km s^{-1} to (V_{center} − 3ΔV) are taken as foreground molecular cloud emission. Stars toward which the foreground emission is larger than 3 K km s^{-1} were removed. Although it is possible that some clouds are farther than the targeted molecular cloud, removing those stars would only make the background baseline more reliable, which does no harm to the distance calculation. This step would largely guarantee that the first jump point along the line of sight is due to the targeted molecular cloud.

The upper threshold of CO emission toward off-cloud stars (the noise level) is set as 1.5 K km s^{-1} (~1.5σ), above which off-cloud stars were removed, while the lower threshold of CO emission toward on-cloud stars (the signal level) was 3–5 K km s^{-1}, below which on-cloud stars were removed. In some cases, lower signal levels (3 K km s^{-1}) were used to include more on-cloud stars to obtain robust statistical results. In total, we examined 400 molecular clouds and derived distances to 28 of them. Five reasons are responsible for unsuccessful distance calculations. First, many molecular clouds are too weak to cause detectable AV or AG. Second, some near molecular clouds have too few foreground stars, and

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Figure 6. Regions (a) before and (b) after one step of two-dimensional dilation. In the dilation, larger label numbers are preferred when multiple clusters are present in the neighborhood of unlabeled pixels. After dilation, the area of the regions becomes larger.
their distances cannot be firmly constrained. Third, a number of molecular clouds have no clear boundaries, and no nearby off-cloud regions are available. Those clouds are possibly associated with adjacent components. Fourth, many molecular clouds have heavy foreground emission, and both the \(A_V\) and \(A_G\) data are truncated. Fifth, there are molecular clouds that are too far (>2.5 kpc) to be local components, and no separation of on- and off-cloud objects was seen. We started from molecular clouds that have larger angular areas and stopped calculating when 100 consecutive molecular clouds have had no distance detection. Results of the 28 molecular clouds are presented in Section 3.1.

3. Results

This section presents the distances and statistical properties of molecular clouds. Statistics include the total number of molecular cloud samples, the equivalent line width, the peak brightness temperature, the physical area, and the mass. The variation of statistical results with different molecular cloud definitions is gauged by changing cutoffs, connectivity types, and MinPts values. Generally, we have three types of molecular cloud samples: (1) relatively large molecular clouds only used for distance examination produced with SCIMES (extended to 2\(\sigma\) level), (2) samples with small molecular clouds produced with SCIMES, and (3) samples produced with DBSCAN. Statistics are based on DBSCAN samples, the second type of sample is only used for comparison.

3.1. Distances

We present distance results for 28 local molecular clouds in the first Galactic quadrant. \(A_G\) is used for 20 molecular clouds, while the remaining 8 were derived with \(A_V\) (Andrae et al. 2018). For both \(A_V\) and \(A_G\), we require that the jump point be evident and the background on-cloud stars clearly above the baseline. As examples, in Figure 7, we demonstrate distances to two molecular clouds, G029.6+03.7 (\(A_G\)) and G043.3+03.1 (\(A_V\)).

Table 1 summarizes the distance results for the 28 molecular clouds. The nearest distance to those molecular clouds is 261 pc, while the farthest one is 1348 pc. From left to right, we display the name (1), averaged \(l-b\)-V position (2, 3, 4), the angular area (5), Gaia DR2 distances (6), number of on-cloud stars (7), minimum CO emission of on-cloud stars (8), maximum distances to on-cloud stars (9), molecular cloud masses (10), kinematic distances (11), the extinction used (12), and notes (13). The molecular cloud masses are estimated by assuming a \(^{12}\text{CO}\)-to-H\(_2\) mass conversion factor of \(X = 2.0 \times 10^{20} \text{ cm}^{-2} (\text{K km s}^{-1})^{-1}\) (Bolatto et al. 2013), and the kinematic distances are derived with the AS model of Reid et al. (2014). The systematic distance error is about 5\% (Yan et al. 2019b; Zucker et al. 2020), which is possibly larger for far-distance molecular clouds (>1 kpc).

Figure 8 describes the face-on distribution of the 28 molecular clouds and the relationship between the distance and the radial velocity. The 28 molecular clouds are certainly incomplete, and for each line of sight, only distances to the nearest molecular clouds were derived. However, those clouds show a quite clear linear correlation between the distance and the radial velocity, which is \(D/\text{kpc} = \left(0.033 \frac{V_{LSR}}{\text{km s}^{-1}} + 0.180\right)\). The parameters were derived from Bayesian analysis and Markov Chain Monte Carlo (MCMC) sampling with both errors in radial velocities and distances considered, including the 5\% systematic error in distances.

A comparison of Gaia DR2 distances and near-kinematic distances is shown in Figure 9. Kinematic distances have two problems: (1) the errors are too large for molecular clouds with a small magnitude of \(V_{LSR} (|V_{LSR}| < 10 \text{ km s}^{-1})\), and (2) it is hard to distinguish the near and far distance ambiguity. We only use near distances because Gaia DR2 distances suggest that they are local. For molecular cloud samples with \(V_{LSR} \geq 10 \text{ km s}^{-1}\), kinematic distances are systematically larger than Gaia DR2 distances by about 0.43 kpc (Reid et al. 2014), 0.15 kpc with the updated model of Reid et al. (2019). This systematic shift indicates that the motion of local molecular clouds (>1 kpc) may not precisely follow the Galactic rotational curve. However, most kinematic distances are compatible with Gaia DR2 distances within errors.

3.2. Cloud Samples

Figure 10 displays cloud identification cases with DBSCAN at the 1 K cutoff with the smallest MinPts for each connectivity type. The results of the three connectivity types are almost identical, except for a few small-size molecular clouds, indicating that the cloud identification is robust against connectivity types. It is worth noting that DBSCAN is able to pick up weak emissions with small MinPts values.

Figure 11 demonstrates the total number of molecular clouds with respect to 11 CO cutoff cases and three connectivity types. For each connectivity type, molecular cloud numbers increase with MinPts. This is because higher MinPts values require strong connections, and structures seen with low MinPts would be decomposed by high MinPts.

Interestingly, with low values of MinPts, molecular cloud numbers decrease toward both high- and low-CO cutoffs. The decrease of trunk numbers toward high-CO cutoffs is reasonable, because molecular clouds with low brightness temperature are washed out, and the break-up of the large molecular clouds cannot fully compensate for this effect. However, the molecular cloud trunk number also decreases at the lower cutoff ends (<3\(\sigma\)). This may be due to three reasons. First, molecular clouds are incomplete because weak CO emission is overwhelmed by noise. Second, the boundary of many molecular clouds is not resolved by the beam size (~50\(\text{arcsec}\)) and small CO cutoff values combine many molecular clouds into single trunks in low brightness temperature regions. Third, it is possible that there are widely distributed diffuse molecular clouds between more condensed molecular clouds, which are all connected under high-sensitivity observations.

For high-CO cutoffs, SCIMES cluster numbers are close to that produced with DBSCAN (at low MinPts), but increase significantly toward the low-CO cutoff end. This is because large molecular clouds were already decomposed at high-CO cutoffs—the SCIMES results resemble DBSCAN clusters. However, at low-CO cutoffs, SCIMES splits large dendrogram trunks, producing many more clusters than DBSCAN with low values of MinPts.

3.3. Equivalent Line-width and Peak Distribution

We now display the distributions of the equivalent line width and the peak brightness temperature of molecular clouds. As
shown in the averaged spectra of nine representative molecular clouds in Figure 12, many spectra cannot be described with single Gaussian profiles, so we used the equivalent line width as a measure of the velocity dispersion. The equivalent line width is defined as

\[ W_e = \frac{1}{T_{\text{peak}}} \sum_i T_i \Delta v, \]

Figure 7. Distances to two molecular clouds, G029.6+03.7 with \( A_G \) (a) and G043.3+03.1 with \( A_V \) (b). On the right-hand-side plots of both panels, the red line is the baseline obtained with off-cloud stars, and the broken horizontal purple line is the extinction variation of on-cloud stars after subtracting the baseline. In the cloud CO image insets, the green and light-blue points represent samples of on- and off-cloud stars, respectively. The red lines delineate the area range of molecular clouds, while the green lines are the lower threshold of CO emission toward on-cloud stars. In the image insets of panel (a), the off-cloud region is selected to be close to the on-cloud region to accurately remove irregular extinction variations of on-cloud stars. The left corner maps are the MCMC sampling results of five parameters: the distance \( D \), the mean and standard deviation of foreground extinction \((\mu_1\) and \(\sigma_1\)), and the mean and standard deviation of background extinction \((\mu_2\) and \(\sigma_2\)). See Yan et al. (2019a) for other details.
where $T_e$ is the brightness temperature of the average spectra in each velocity channel, $\Delta V = 0.2$ km s$^{-1}$, and $T_e$ peak is the peak brightness temperature of the averaged spectra.

The top panel of Figure 13 describes the equivalent line-width distribution, and another measurement of the velocity dispersion, the second moment, is also shown as a comparison. The range of the equivalent line width is about 0.2–10.0 km s$^{-1}$. For low MinPts cases, the equivalent line width shows a similar distribution to that of the Gaussian component samples identified by Riener et al. (2020) from the entire Galactic Ring Survey $^{13}$CO ($J = 1 \to 0$) data using the GaussPy+ algorithm (see Figure 8 therein). However, with high MinPts, DBSCAN identifies many bright regions as independent molecular clouds, and the number of molecular clouds with small equivalent line widths increases sharply.

The peak position of the equivalent line-width distribution shifts left slightly from the $2\sigma$ (solid lines) to $7\sigma$ (dashed lines) cutoffs. Two processes are responsible for this shift: (1) the removal of low-CO emission in the envelope would decrease the equivalent line width, and (2) high-CO cutoffs break up large molecular clouds into ones with small equivalent line widths, compensating the effect of the first process. Due to the second process, the peak shifting with high-CO cutoffs is not evident, and low-CO cutoffs produce more molecular clouds with large equivalent line widths.

The bottom panel of Figure 13 demonstrates the peak intensity distribution. The peak brightness temperature distribution resembles an exponential distribution above the threshold. As seen in panel (b) of Figure 13, observations are incomplete due to the truncation caused by the post-selection criteria, and the behavior of the peak brightness temperature toward the lower value end is unknown. CO cutoffs affect the peak distribution significantly, because molecular clouds with low peak intensities are removed by high-CO cutoffs and the post-selection criteria. The break-up of large molecular clouds increases the number of molecular clouds with moderate peak brightness temperatures.
3.4. Physical Area Distribution

In this section, we describe the physical area distribution of molecular clouds. The molecular cloud distances are estimated with the distance and radial velocity relationship (see Figure 8), and the residual distance dispersion (161 pc) is used as the distance error, which is the only error source considered. Typically, the relative error of the physical area is about 50%. Molecular clouds nearer than 200 pc or farther than 1500 pc are excluded from the statistics, due to the uncertainty of extrapolation.

The minimum physical area of molecular clouds is about 0.01 pc², and the maximum physical area is about $1 \times 10^5$ pc². The dynamic range of the physical area is $\sim 10^6$, which enables us to gauge the area distribution robustly. As to the angular area, the smallest molecular cloud only has one beam size (4 pixels), while the largest one occupies more than half of the entire surveyed region. The largest molecular cloud is mainly the Aquila Rift and is contaminated by some molecular clouds from the Perseus arm.

As shown in Figure 14, the physical area shows a power-law distribution. This power-law distribution is insensitive to algorithms and parameters. Even for SCIMES clusters, which miss a large portion of CO emission in the envelope, the area distribution is still present. We fitted the index of each case with a truncated power-law model (with a minimum threshold), and derived the index with Bayesian analysis and MCMC sampling.

Figure 8. Face-on view of 28 molecular clouds with well-determined distances. Colors in both panels represent the magnitude of radial velocities, and the 5% systematic error is included in the distance error bars. The error of $V_{LSR}$ is the second moment of velocities. With Bayesian analysis and MCMC sampling, we derived a relation of $\frac{D}{\text{pc}} = (0.033 \frac{V_{LSR}}{\text{km s}^{-1}} + 0.180)$ between the distance and $V_{LSR}$, and the distance scatter around this linear relationship is about 0.161 kpc. In the right-hand-side plot, the dashed and dotted black lines represent the kinematic distance curve (Reid et al. 2014) with respect to $V_{LSR}$ toward $l = 25^\circ$ and $l = 50^\circ$ in the midplane ($b = 0^\circ$), respectively. A methanol maser source, G035.19–00.74 (Zhang et al. 2009; 2.19 kpc at 30 km s$^{-1}$), does not follow this linear relationship but is closer to the kinematic distance. The distance to the Galactic center is 8.178 kpc (Gravity Collaboration et al. 2019).

Figure 9. A comparison of Gaia DR2 and near-kinematic distances to 28 local molecular clouds in the first Galactic quadrant. Panel (a) shows the comparison results with the A5 model of Reid et al. (2014), while panel (b) shows that with an improved version from Reid et al. (2019). For molecular clouds at $V_{LSR} \geq 10$ km s$^{-1}$, the systematic shift of kinematic distances with respect to Gaia DR2 distances is 0.43 kpc for panel (a) and 0.15 kpc for panel (b). The 5% systematic error is included in Gaia DR2 distance error bars.

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As shown in Figure 14, the physical area shows a power-law distribution. This power-law distribution is insensitive to algorithms and parameters. Even for SCIMES clusters, which miss a large portion of CO emission in the envelope, the area distribution is still present. We fitted the index of each case with a truncated power-law model (with a minimum threshold), and derived the index with Bayesian analysis and MCMC sampling. The complete threshold of the physical area, $A_{\text{min}}$, is estimated by assuming 4 pixels is the minimum resolved angular area, and according to the distance range (0.25–1.5 kpc; see Section 3.1), 4 pixels at 1.5 kpc corresponds to 0.19 pc², i.e., $A_{\text{min}} = 0.19$ pc².
Consequently, only molecular clouds that have physical areas larger than 0.19 pc$^2$ are used in the power-law fitting.

Maser parallax measurements (Reid et al. 2019; Zhang et al. 2019) show that part of the molecular clouds ($-6$ to $30$ km s$^{-1}$) are located in the Perseus arm ($>8.8$ kpc). The contamination of the Perseus arm molecular clouds may cause systematic errors in the $\alpha$ index. Given the far distances and small filling factors, the angular area of molecular clouds in the Perseus arm is relatively small, and many are locked in the largest molecular cloud; consequently, the contamination of the Perseus arm molecular clouds is negligible.

The power-law distribution is defined as

$$dN \propto A^{-\alpha} dA,$$

where $A$ is the molecular cloud physical area. The normalized probability density function (PDF) for each molecular cloud (no errors considered) is

$$P(A_i | \alpha) = (\alpha - 1) A_{\text{min}}^{\alpha - 1} A_i^{-\alpha},$$

where $A_i$ is the physical area of a molecular cloud. However, if the error of $A_i$, $\Delta A_i$, were considered, the PDF would be the convolution (Koen & Kondlo 2009) of the error distribution with Equation (4), which is

$$P(A_i, \Delta A_i | \alpha) = \int \frac{1}{\Delta A_i \sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{A_i - x}{\Delta A_i} \right)^2 \right) P(A_i - x | \alpha) dx,$$
where $x$ is the $A_i$ error, whose PDF is assumed to be Gaussian with a mean and standard deviation of $A_i$ and $\Delta A_i$, respectively. The total probability is the product of PDFs of all physical areas, and the involvement of the integration, which has no closed-form expression, makes the MCMC sampling slow. Consequently, we calculated 50 MCMC sampling chains, each of which contains 40 thinned samples (every 10) and an extra 10 burn in (the first 10 thinned samples were discarded). Consequently, the total sample number is 2000, whose mean and standard deviation correspond to the mean and error of $\alpha$.

Panel (b) of Figure 14 displays the $\alpha$ derived with different CO cutoffs and algorithms. The standard deviation of each $\alpha$ derived from MCMC sampling for each case is approximately equal (~0.03), so we took the unweighted mean of all $\alpha$ as the estimated value (2.20) and convolved the MCMC error to the unweighted standard deviation of all $\alpha$ (only with DBSCAN) as the total error (0.18), i.e., the estimated $\alpha$ is $2.20 \pm 0.18$. SCIMES results are not included. The $\alpha$ shows a systematic variation with respect to CO cutoffs and MinPts, and roughly, it increases slightly toward high-CO cutoffs and large MinPts values. Interestingly, both high-CO cutoffs and large MinPts values correspond to regions with bright $^{12}$CO emission, i.e., diffuse molecular clouds may have different statistical properties from dense molecular clouds.

### 3.5. Mass Distribution

In addition to the physical area, we examined the distribution of the cloud mass. The mass is derived by assuming a $^{12}$CO-to-H$_2$ mass conversion factor of $X = 2.0 \times 10^{20}$ cm$^{-2}$ (K km s$^{-1}$)$^{-1}$ (Bolatto et al. 2013; see Table 1). The minimum and maximum cloud mass is about 0.05 and $5 \times 10^5 M_\odot$, respectively, and the relative mass error is typically 50%.

We first examined the total flux reconstructed from the molecular clouds identified with DBSCAN and SCIMES. As demonstrated in Figure 15, for each cutoff, the total flux of $^{12}$CO is calculated based on the noise-masked spectral data with the 1 K ($2\sigma$) cutoff and the smallest MinPts values for each connectivity type. For a specific cutoff, the total flux is the...
sum of all voxel (noise-masked) brightness temperatures multiplied by 0.2 km s\(^{-1}\) \(\Omega_A\), where \(\Omega_A\) is the solid angle of a single voxel.

Strikingly, as shown in Figure 15, the total flux of \(^{12}\)CO increases approximately linearly with the decrease of the \(^{12}\)CO cutoff, and there is no sign of completeness at the low-\(^{12}\)CO cutoff end. The total flux can be approximated by \((-6.5 \times 10^6 \frac{\text{cutoff}}{[\text{K}]} + 3.2 \times 10^7)\) K km s\(^{-1}\) \(\Omega_A\). This indicates that despite being weak (<2 K, 4\(\sigma\)), the \(^{12}\)CO emission around molecular clouds collectively has the same order of magnitude as the strong emission (>2 K) due to the large volume. Clearly, observations with a sensitivity of 0.5 K are still incomplete for local molecular clouds (<1.5 kpc).

DBSCAN recovers most of the flux in cases with small MinPts values, but SCIMES misses a significant fraction (about 55%) at the lower \(^{12}\)CO cutoff end (<2.5 K). The maximum flux of molecular clouds is about \(2.4 \times 10^7\) K km s\(^{-1}\) \(\Omega_A\), and the dynamic range of the flux is about \(10^6\) (the minimum flux is about 4 K km s\(^{-1}\) \(\Omega_A\)). DBSCAN shows that the molecular cloud that has the highest flux occupies about 92% of the total flux at the 2\(\sigma\) cutoff and decreases to 42% at the 7\(\sigma\) cutoff.

Interestingly, the statistical properties of molecular clouds can be revealed by a large number of small independent structures, which collectively occupy a tiny portion of the total flux in PPV space.

In Figure 16, we display the integrated intensity map of all DBSCAN (MinPts = 4 and connectivity = 1) molecular clouds at the 2\(\sigma\) cutoff. As a comparison, we display the integrated intensity map of the largest molecular clouds, which contains about 92% of the total molecular cloud flux. The main component of the largest molecular cloud is the Aquila Rift, and evidently, it contains a fraction of emission from the Perseus arm near the Galactic midplane.

Panel (a) of Figure 17 displays the mass distribution of molecular clouds identified with DBSCAN and SCIMES. Figure 17 shows a power-law distribution, and we fitted the power-law index with the same procedure used on the physical area, which is displayed in panel (b) of Figure 17. The complete threshold of the mass is estimated with the minimum flux \((16 \times \text{cutoff} \times 0.2 \text{ km s}^{-1})\) at 1.5 kpc. The systematic variation of the mass power-law index with respect to \(^{12}\)CO cutoffs and MinPts values is more evident than that of the
physical area, and the average power-law index, $1.96 \pm 0.11$, of the mass distribution is slightly flatter than that of the physical area.

4. Discussion

In this section, we compare our results with previous studies, including molecular cloud properties and their distances.

4.1. DBSCAN versus HDBSCAN

In addition to DBSCAN, HDBSCAN, an improved version of DBSCAN, is also able to perform clustering. We compared these two algorithms and conclude that HDBSCAN is not suitable to identify consecutive structures in PPV space. Consequently, we used DBSCAN instead of HDBSCAN.

HDBSCAN adjusts the value of $\varepsilon$ according to the density of points, i.e., the definition of molecular clouds is not uniform and changes with regions. As shown in Figure 18, HDBSCAN misses significant flux in dense regions due to high point densities (corresponding to small $\varepsilon$), while in sparse regions, HDBSCAN collects loosely bound (corresponding to large $\varepsilon$) points as clusters. In addition, we found that HDBSCAN cluster results depend on the $l$–$b$–$V$ range of the input data cube, which is also a common problem with SCIMES.
4.2. Molecular Cloud Distances

In this section, we compare Gaia DR2 distances with previous studies.

Eight maser sources (Zhang et al. 2009, 2013, 2019) with distances derived from trigonometric parallaxes are located in the $l$–$b$–$V$ space of local molecular clouds, but they are all too far to be local components. Seven of those masers are located in the Perseus arm ($0 \leq V_{\text{LSR}} \leq 30$ km s$^{-1}$ and $D > 8.85$ kpc), and the remaining one, G035.19–00.74 (Zhang et al. 2009), belongs to the Sagittarius arm. Due to the far distance or heavy foreground extinction, none of the eight maser sources has extinction distance measured. The distance to G035.19–00.74 is about 2.19 kpc (at 30 km s$^{-1}$), which shows large deviations from the linear relationship between the local distance and the radial velocity, but the distance to G035.19–00.74 is closer to the kinematic distance. Consequently, although in the same $l$–$b$–$V$ space, some molecular clouds are not local.

G029.6+03.7 contains a nearby H II region, W40, which is known in the Serpens molecular cloud. The Gaia DR2 distance to G029.6+03.7 is $547 \pm 39$ pc, while the Very Long Baseline Array parallax measurements (Ortiz-León et al. 2017) show that the distance to W40 is $436 \pm 9$ pc. However, the W40 region is complicated, and no close off-cloud regions are available. As shown in panel (a) of Figure 7, the selected region is about $5^\circ$ to the left of W40. At a distance of 436 pc, $5^\circ$ corresponds to about 40 pc, suggesting that the 100 pc difference is reasonable. This also shows that the size of molecular clouds can be as large as 100 pc along the line of sight, and small subregions may not be able to represent averaged distances to large molecular clouds. This distance dispersion is consistent with the results of Herczeg et al. (2019) and Zucker et al. (2020).
4.3. Number of Molecular Cloud Samples

An important step toward understanding molecular clouds is to obtain a complete census of their population. However, unlike stars, molecular clouds are extended sources, and their total number depends on tracers, definitions, and observation qualities.

In the surveyed 239 deg$^2$ region, the number of clouds per square degree is about 19 according to the results of connectivity 1 (MinPts 4). Colombo et al. (2019) identified about 85,000 clouds in the first Galactic quadrant (10$^\circ$.25 < l < 17$^\circ$.5 and |b| ≤ 0$^\circ$.5, 17$^\circ$.5 < l < 50$^\circ$.25 and |b| ≤ 0$^\circ$.5, and 50$^\circ$.25 < l < 55$^\circ$.25 and |b| < 0$^\circ$.5) from COHRS (Dempsey et al. 2013), and 5229 of those 85,000 clouds are in the local l–b–V space. Colombo et al. (2019) found many more clouds (in a much smaller region) because they split large trunks into small components with SCIMES, and furthermore, $^{12}$CO (J = 3 → 2) requires high-temperature environments to excite and is less crowded in l–b–V space.

Rice et al. (2016) provided a uniform catalog of 1064 massive molecular clouds based on the CfA–U.Chile $^{12}$CO (J = 1 → 0) survey (Dame et al. 2001), and the technique they used is the dendrogram. Only 16 of those molecular clouds are located in the l–b–V space of local molecular clouds. However, using the same data set but only focusing on the Galactic plane (|b| < 5$^\circ$), Miville-Deschênes et al. (2017) found 8107 molecular clouds using an alternative algorithm, which combines hierarchical cluster identification and Gaussian decomposition, and 380 molecular clouds are located in the local l–b–V space. The large beam size (about 8$'$) of the CfA–U.Chile CO survey overwhelms many small-size ones.

According to the DBSCAN and SCIMES results, DBSCAN is useful for detecting consecutive structures in PPV space, while SCIMES is capable of splitting large molecular clouds into medium ones. In the first Galactic quadrant, DBSCAN collects a large portion of PPV voxels into single large
molecular clouds with low MinPts values, while SCIMES splits this large structure into small-size ones, producing many more molecular clouds than DBSCAN. However, in the second and third Galactic quadrants, where molecular clouds are not crowded in PPV space, DBSCAN and SCIMES results would be similar.

The molecular cloud samples detected by the MWISP CO survey are still incomplete. The turnover of molecular cloud numbers with small MinPts (see Figure 11) near 3σ may be due to low signal-to-noise ratios. By extrapolating the linear relation between the CO cutoff and total flux described in Figure 15 to 0 K, the maximum flux is estimated to be 3.23 × 10^7 K km s^{-1} Ω_{⊙} at the sensitivity of the PMO 13.7 m telescope, meaning that the 2σ cutoff collects about 80% of the total flux (70% for the 3σ cutoff). Compared to higher sensitivity telescopes, the PMO 13.7 m telescope may still miss a significant part of the flux.

4.4. The Physical Area and Mass Distribution

The spectra of the physical size (Colombo et al. 2019) and the mass (Rice et al. 2016) of molecular clouds are characterized by power-law distributions. However, as demonstrated by the DBSCAN results, the physical area and mass distributions generally conform to a power law, but their indices vary systematically with the DBSCAN parameters and the CO cutoffs.

The statistics of DBSCAN molecular clouds show significant difference from previous results. On average, the power-law index of the physical area is about −2.20, and the corresponding index of the molecular cloud size is about −3.40, which is steeper than the value −2.8 obtained by Colombo et al. (2019) with SCIMES. The power-law index of the mass spectrum is about −1.96, which is moderate compared with that (−2.2) found by Rice et al. (2016) with a uniform catalog built on a large-scale Galactic $^{12}$CO ($J = 1 \rightarrow 0$) survey (Dame et al. 2001) using the dendrogram and with that (−1.70) found by Colombo et al. (2019) with the $^{12}$CO ($J = 3 \rightarrow 2$) line using SCIMES.

The variation of the power-law index can be attributed to multiple causes. Apart from the tracing transition lines, algorithm parameters, the distance errors, and regions, another factor that may significantly affect the molecular cloud size and mass distribution is the filling factor. The filling factor is related to the sensitivity and resolution of the telescope and some intrinsic properties of molecular clouds, such as the column density distribution and the peak brightness temperature. We will examine the distance and the filling factor effect once we have collected sufficient molecular cloud samples with accurate distances derived from the Gaia stellar parallax and extinction measurements.

5. Summary

We used the DBSCAN algorithm to decompose the $^{12}$CO spectral cube of local components (−6 to 30 km s^{-1}) in the first Galactic quadrant into individual molecular clouds, and investigated the statistical properties and distances of molecular clouds. We define molecular clouds as independent consecutive structures in l-b-V space, which is robust against the criteria of DBSCAN. At the 1 K (2σ) emission level and with small MinPts, the number of local molecular clouds per square degree is about 19. For CO cutoffs less than 2 K, SCIMES discards about 55% of the total flux in order to split large dendrogram trunks that are connected by diffuse CO emission.

We derived distances to 28 molecular clouds, most of which have their distances accurately determined for the first time. Distances to molecular clouds are in the range of 250–1500 pc, and the distance shows a linear relationship with the radial velocity. Gaia DR2 distances indicate that the kinematic distances may be systematically larger for local molecular clouds in the mapped region.

The linear relationship between the cutoff and the total flux indicates a completeness of about 80% for the flux collected from local molecular clouds. The largest molecular cloud has an area of ~130 deg2, occupying 92% of the total flux. The physical area of molecular clouds shows a power-law distribution with an index of about −2.20 ± 0.18, which changes slightly with cutoffs. The molecular cloud mass shows a power-law distribution as well, and the index is about −1.96 ± 0.11.

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Facilities: PMO 13.7 m, Gaia.
Software: astropy (Astropy Collaboration et al. 2013), Miriad (Sault et al. 1995), astrodendro, scipy.

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