Assessing membership projection errors in star forming regions

T. Roland, C. M. Boily, and L. Cambrésy

Université de Strasbourg, CNRS, Observatoire Astronomique de Strasbourg, UMR 7550, 67000 Strasbourg, France
e-mail: timothe.roland@astro.unistra.fr

Received 6 August 2020 / Accepted 19 October 2020

ABSTRACT

Context. Young stellar clusters harbour complex spatial structures emerging from the star formation process. Identifying stellar overdensities is a key step in better constraining how these structures are formed. The high accuracy of distances derived from Gaia DR2 parallaxes still do not allow us to locate individual stars within clusters of ≈1 pc in size with certainty.

Aims. In this work, we explore how such uncertainty on distance estimates can lead to the misidentification of membership of sub-clusters selected by the minimum spanning tree (MST) algorithm. Our goal is to assess how this impacts their estimated properties.

Methods. Using N-body simulations, we build gravity-driven fragmentation models that self-consistently reproduce the early stellar configurations of a star forming region. Stellar groups are then identified both in two and three dimensions by the MST algorithm, representing respectively an inaccurate and an ideal identification. We compare the properties derived for these resulting groups in order to assess the systematic bias introduced by projection and incompleteness.

Results. We show that in such fragmented configurations, the dynamical mass of groups identified in projection is systematically underestimated compared to those of groups identified in 3D. This systematic error is statistically of 50% for more than half of the groups and reaches 100% in a quarter of them. Adding incompleteness further increases this bias.

Conclusions. These results challenge our ability to accurately identify sub-clusters in most nearby star forming regions where distance estimate uncertainties are comparable to the size of the region. New clump-finding methods need to tackle this issue in order to better define the dynamical state of these substructures.

Key words. methods: statistical – stars: formation – stars: kinematics and dynamics – open clusters and associations: general

1. Introduction

Young stars are predominantly observed in the dense parts of spiral arms of disc galaxies. After a decade of Herschel observations, it is now established that these star forming regions exhibit highly sub-structured configurations due to fragmentation of the gas in extended filaments (André et al. 2010; Pokhrel et al. 2018). The latest interferometric facilities (e.g., ALMA, NOEMA) allow to study filaments and primordial cores at sub-parsec scales (see e.g., Hacar et al. 2017, 2018; André et al. 2019; Montillaud et al. 2019), bringing to light the extended 3D structures of the Orion A tail, reporting an estimated total length of 90 pc, in significant disagreement with the projected size of 40 pc. Other large, extended structures have also been identified outside the solar circle (e.g., Alves et al. 2020). The astonishing accuracy of Gaia DR2 data peaks at 5 mas, which corresponds to ≈8 pc at this distance (≈400 pc).

In this context, simulations are key to testing our understanding of the processes acting in these fragmented regions. Recent computations of hydro-gravitational fragmentation and accretion, coupled with radiation-transfer physics, give promising results in terms of for example the shape of the stellar mass function (e.g., Bate 2012), formation of proto-planetary discs (e.g., Hennebelle et al. 2016), and the role of stellar feedback (e.g., Wall et al. 2020). Despite continued progress, the number of young stars produced in these high-resolution calculations is limited to a few hundred. Larger calculations remain challenging. Moreover, strong interactions between newly born stars occur in these simulations. Exploring the interplay between several of these systems is key to probing the formation of more massive clusters. Consequently, pure N-body modelling is still of great use to explore configurations with N > 1000 stars. This approach works well when gravity takes over magneto-thermal support and drives the fragmentation of the giant molecular cloud (GMC). This allows us to address specific topics such as primordial mass segregation (Pavlik et al. 2019) or the impact of gradual star formation (Farias et al. 2019). As massive clusters are also likely to form massive stars (Motte et al. 2018), N-body simulations are also suited to exploring the environment where they form.

There is a long-standing history of modelling stellar interactions with gravity alone. One major challenge of such work consists in generating realistic initial configurations. Different methods have been developed. One of the most straightforward is to follow snapshots of hydro-dynamical simulations and...
the structures traced by sink particles (e.g., Moeckel & Bate 2010; Fuji & Portegies Zwart 2016). This approach is well suited to exploring the long-term evolution of the original hydro-dynamical simulations, but is limited by the high computational effort to model the full star formation process. An efficient alternative that can be used to reproduce the fragmented aspect of star forming complexes at lower cost was introduced by Goodwin & Whitworth (2004), namely the box fractal method. This technique can recreate spatial configurations of various observed clusters and allows the user to tune the different levels of substructures. However, the velocity field is not constrained by the history of formation of such structures which makes the dynamical state of the system somewhat ad hoc.

Another method providing a balance between computational cost and realistic configurations was proposed by Dorval et al. (2016), which we refer to as gravity-driven fragmentation (GDF) models. This method is an efficient way to build fragmented initial conditions self-consistently using only N-body modelling. It allows a self-gravitating system uniformly populated by stars to be isotropic with respect to the barycentre of the system; its velocity field is chosen so that the expansion stops roughly when the system is 4 pc in diameter, resulting in a mean density of $\rho_0 \approx 150 M_\odot \text{pc}^{-3}$.

In this paper, we specifically discuss morphological biases introduced when estimating properties of stellar over-densities in a fragmented cluster seen in projection. We used the GDF method to model a realistic distribution of stars in a young star cluster (Sect. 2). Our methodology consists in identifying stellar groups of more than 50 members (also referred to as clumps), both in 3D and in projections (2D) and estimating their properties (Sect. 3). We used the virial dynamical mass to compare groups identified by both methods and assess the deviation introduced by projection effect (Sect. 4). Finally, we discuss the implications of our results in Sect. 5 and conclude in Sect. 6.

2. Building realistic stellar distribution

2.1. Gravity-driven fragmentation modelling

We start our study using the GDF models described in Dorval et al. (2016). We summarise here the motivations and principles of such models.

The fragmentation of a continuous cold fluid bound by gravity will proceed from continued growth of a spectrum of perturbations. When dealing with stars, the point-mass nature and limited number of elements means that the potential is not smooth, and Poisson-seeded density fluctuations rapidly develop into dense substructures. The growth of small-scale modes will proceed on very short timescales, however large-scale modes into dense substructures. The growth of small-scale modes will smooth, and Poisson-seeded density fluctuations rapidly develop and limited number of elements means that the potential is not perturbations. When dealing with stars, the point-mass nature of gravity will proceed from continued growth of a spectrum of substructures. However, the velocity field is not constrained by the history of formation of such structures which makes the dynamical state of the system somewhat ad hoc.

As most of the stars in a GMC are formed within a free-fall time (Grudic et al. 2018), this allows us to study the very early stages of the configuration of newly born stars. These structures have not yet been erased by two-body relaxation, and their dynamical state is a direct result of the fragmentation process.

We perform the computations with the AMUSE platform (Portegies Zwart & McMillan 2018). We used the N-body code

\[ t_f = \frac{\sqrt{\frac{3\pi}{32G\rho_0}}}{\rho_0} = 0.67 \text{Myr}. \] (1)

As the overall velocity field is self-consistently built, we are able to probe their dynamical state and interactions with their surroundings. Furthermore, when using a mass spectrum, the most massive stars attract the surrounding low-mass stars to themselves. Dorval et al. (2016) showed that massive stars are the seeds for the growth of fragment modes. As a result, clumps are mass segregated at birth, retrieving a key feature of hydro-simulations (e.g., Maschberger & Clarke 2011; Wall et al. 2019). They also harbour a top-heavy mass profile whose Salpeter index is comparable to the one found in young- and open clusters of the Milky Way (Bastian et al. 2010). Figure 1 shows the initial, intermediate, and final steps for one of our models. More details and further examples are given in Dorval et al. (2016, 2017).
ph4 which is a fourth-order Hermite scheme integrator coupled with the Multiple module to handle efficiently close interactions (Hut et al. 1995; McMillan & Hut 1996). The relative energy drift $\delta E/E$ at each time-step is always lower than $10^{-6}$ except when close encounters cannot be resolved by the Multiple module, and can lead to an error up to $10^{-4}$. However, these remain rare, which makes the total energy drift during the whole calculation of the order of $10^{-4}$. We do not explicitly include any binary population but they are able to form dynamically through the fragmentation process. However, the fraction of multiple stars remains below 5% and these do not influence our conclusions.

2.3. Sub-selection within the GDF model

Gravity-driven fragmentation models allow exploration of the structures built by the fragmentation process. In this study, we specifically target clumps that can be misidentified when only seen in projection. However, as we see in Fig. 1, the spherical imprints of the initial conditions remain visible at the large scale. This overall geometry of the cluster can have an impact on the clumps that we identify in projection in the following section.

To this end, we implemented a method to extract a subsample from the central parts of the system. This method is based on the HOP algorithm (Eisenstein & Hut 1998) which was initially designed to identify over-dense haloes in any particle-based sample. HOP assigns to each particle a local density estimate based on a list of nearest neighbours and groups them around density peaks. We adapted the HOP algorithm to select a sample representative of the complex structure of the GDF model spanning a large-enough range in density. First, we tune the parameters to select only particles with a local density above a given threshold. Several tests lead us to set the threshold value equal to $\approx 75\, M_\odot\, pc^{-3}$, or half of the median system density. We then exclude groups that were close to the edge of the GDF sphere by retaining only those that included at least one member lying less than 1 pc from the centre of the model. This two-step procedure leads to the selection of a subsample of particles excluding about half of the stars.

This new sample is the reference set for the rest of the study. Figure 2 shows three orthogonal views of the initial GDF model (grey dots) and the selection of 7235 stars (orange dots). On the upper left panel, local densities of particles within a slice of the model (black rectangles) are plotted. This highlights that the selection retains all the main density peaks. Furthermore, local densities span a large range, from $\approx 100\, M_\odot\, pc^{-3}$ to $\approx 10^4\, M_\odot\, pc^{-3}$.

3. Stellar groups

Stars are more likely to be formed in dense environments where the final collapse of gas is transformed into stars through an accretion process. The various stages of accretion\(^2\) means that

\(^2\) These are known as Class 0, I, II, III objects (see e.g., Andre et al. 2000).
stars acquire their mass in a shared environment. Data from Herschel for example have long indicated that the proximity of young stars gives rise to extended structures of varying morphology, all interconnected by a complex network of bridges and filaments. We are tasked with identifying the stars that belong to such a network.

3.1. Identification method

Several techniques have been developed to detect over-densities in observations of star forming regions. These include, for example, the minimum spanning tree (MST) algorithm (Gutermuth et al. 2009); the finite-mixture model technique (Kuhn et al. 2014); DBSCAN (Joncour et al. 2018), and HDBSCAN (Kounkel et al. 2018). Despite their specific features, most of these techniques rely on star number density estimates projected on the sky. This is mainly because of the few observables available in such crowded regions, where extinction may be significant. By construction, these methods may miss the true underlying 3D structure of the objects under study.

We address the biases that arise from projection effects, focusing on the MST method. Its ability to detect over-dense structures of any shape makes it a powerful tool in studies of star forming regions. It has been widely used by both theorists (e.g., Maschberger et al. 2010) and observers (e.g., Kirk & Myers 2011; Beuret et al. 2017). MST statistics can also be used to derive other properties of stellar clusters such as morphological aspects (Cartwright & Whitworth 2004) or a measure of mass segregation (Allison et al. 2009). Moreover, the MST method may be adapted to treat either 2D or 3D space distributions. Our setup described below was similarly implemented in both cases. This uniformity in the methodology is crucial in order to avoid introducing additional biases between 2D and 3D identifications.

3.2. Minimum spanning tree setup

We summarise the MST procedure briefly (see e.g., Gutermuth et al. 2009 for further details). A spanning tree is a path linking all particles of a data set without forming closed loops. The MST is the spanning tree that minimises the total length of this path. We thus obtain a hierarchical set of edges that link every particle of the sample. To identify groups, we define a characteristic cut-off scale, \( d_{\text{cut}} \), such that all edges of larger values will be removed from the MST set. This isolates star aggregates that are on average closer to each other. The choice of \( d_{\text{cut}} \) is critical to our analysis: a large value will link together stars that are very widely separated, revealing a few star aggregates that are on average closer to each other. The larger values will be removed from the MST set. This isolates loops. The MST is the spanning tree that minimises the total length retrieved by adding one-half of a standard deviation to the mean value of MST edges. The cutting length \( d_{\text{cut}} \) is set to

\[
d_{\text{cut}} = \text{mean}(E_{\text{MST}}) + \text{std}(E_{\text{MST}})/2, \tag{2}
\]

with \( E_{\text{MST}} \) being the set of MST edges. This way of fixing \( d_{\text{cut}} \) provides nearly optimal values without the iteration procedure.

3.3. Membership \( N \)

We fixed a minimum number of stars per stellar group, \( N \), based on two arguments. The first is that we consider a system that is on the order of 1 Myr old, which is old enough for massive stars to have reached the main sequence, but not so old that the system as a whole has had time to settle into virial equilibrium. Hence, filaments and knots are transient features. On the other hand, we want the majority of these clumps to be as close as possible to their state at formation: indeed, MST statistics cannot be used to gauge the equilibrium state of the substructures we aim to isolate. However, what is clear is that any substructure will evolve internally by phase mixing and kinetic-energy diffusion on a timescale of \( \propto 1/\sqrt{t_0} \). We take as reference an average density of \( 100\,\rho_{\odot}\,pc^{-3} \), with \( \gamma \) being a dimensionless scalar. We then compute a characteristic time \( t_{\text{rel}} \sim 1.5/\sqrt{\gamma} \times 10^7 \) yr, which we take as the dynamical timescale for motion driven by gravity. When a number \( N \) of stars are bound together, their repeated interactions lead to diffusion of kinetic energy on a timescale \( t_{\text{rel}} \) given by (e.g., Meylan & Heggie 1997):

\[
t_{\text{rel}} \approx 0.138 \left( \frac{R_{\odot}}{2R} \right)^2 \frac{N}{\ln 0.4N} t_{cr}. \tag{3}
\]

In the above relation, the ratio of half-mass radius \( R_{\odot} \) to virial radius \( R \) is \( \sim GM/E \) (where \( E \) is the binding energy) is about 1 for self-gravitating configurations near equilibrium. We find \( t_{\text{rel}} > t_{cr} \) for \( N \gtrsim 50 \), and furthermore \( t_{\text{rel}} > 1 \) Myr for \( \gamma < 1 \). This tells us that clumps with membership \( N \geq 50 \) or more should remain relatively close to their phase-space configuration at birth. Even so, the case for setting \( N = 50 \) becomes weaker in denser environments (\( \gamma > 1 \)) and we should increase \( N \) in proportion to \( \sqrt{\gamma} \) to avoid diffusion effects which drive dissolution. Clearly, a setup that will fit all situations is difficult to pin down; our reference value \( N = 50 \) also coincides with the membership of stellar associations seen in the low-density environments (Lada & Lada 2003; Gouliermis 2018). This value is also, in a loose sense, motivated by observations.

3.4. Dynamical mass estimates

We apply the MST algorithm to the subsample defined in Sect. 2.3 twice: once using the full (3D) spatial coordinates, and once using only projected coordinates on the \( xy \) plane. Three orthogonal views of the resulting groups identified in 3D are plotted in Fig. 3, and in 2D in Fig. 4. This leads to the identification of approximately 16 groups in each case. However, the comparison between these figures shows a different identification. In Fig. 3, the main over-densities of the region are well retrieved in all projection panels; we refer to these as real groups, as they represent the ideal identification with the MST algorithm. By contrast, in Fig. 4, group members appear well clumped only in the \( xy \) plane. On the other planes, they spread out over the whole area. These groups, henceforth projected groups, are biased in various ways: they can be real over-densities with some unrelated contaminants; or, completely artificial structures whose

\[\text{There are a few exceptions, for instance: HDBSCAN cited above or the friends-of-friends algorithm (Huchra & Geller 1982) which both use spatial- and kinematic coordinates, but they are difficult to set up.}\]
members are just aligned by chance in the line-of-sight. We emphasize the fact that this is different from the classical contamination by field stars, because all stars in our model are lying within the same star forming region of ≈4 parsec in diameter. Real and projected groups cannot be compared one to one. In order to compare both sets statistically, we quantify an observable property of these groups self-consistently.

With this in mind, we compute the dynamical mass which is a powerful tool to gauge the equilibrium state of a system (Portegies Zwart et al. 2010). It is also used to evaluate the dynamical state of young stellar systems and determine their fate (see e.g., Kuhn et al. 2019). From the virial theorem, we define the dynamical mass $M_{\text{dyn}}$:

$$M_{\text{dyn}} = \eta \times \frac{R_{\text{eff}}^2 \sigma_{\text{LOS}}^2}{G},$$  \hspace{1cm} (4)$$

where $R_{\text{eff}}$ is the effective radius, and $\sigma_{\text{LOS}}$ is the line-of-sight velocity dispersion. The mass-to-light ratio, denoted $\eta$, depends on the phase-space configuration of the stellar system (Boily et al. 2005; Fleck et al. 2006). Hence all quantities that appear on the right-hand side of Eq. (4) are observables from projected data. This is crucial to compare $M_{\text{dyn}}$ for real and projected groups in a self-consistent way.

As groups in our sample are asymmetric and not fully relaxed, we first determine the value of $\eta$ empirically on real groups. This will constitute a value of reference to assess the difference between real and projected groups (we discuss the value of $\eta$ further in Sect. 5.4).

To obtain an ensemble of $\eta$s representative of each group, we estimate the dynamical mass of real groups from a large number of different lines of sight, representing the possible viewing angles all over the sphere. To pick isotropic lines of sight, we chose the HEALPix tessellation (Górski et al. 2005) with the resolution parameter $N_{\text{side}} = 3$, giving 192 different angles of view separated by $\approx 14^\circ$ each. Our procedure iterates over these lines of sight and re-computes the position and velocity of the whole sample to estimate the projected dynamical mass of real groups corresponding to each view. Finally, since the HEALPix tessellation is symmetric with respect to the centre of the sphere, each configuration is paired with its mirror image. As a result there are $192/2 = 96$ independent mass estimates for each real group.

The effective radius in Eq. (4) is often replaced with the half-light radius in observational surveys of star clusters. The half-light radius matches the half-mass radius of analytic King-Michie cluster models in equilibrium (Mengel et al. 2002; Wolf et al. 2010) which allows direct comparison between observations and theory. However, this no longer holds true when the stellar clusters are mass-segregated (Gaburov & Gieles 2008). Moreover, the MST identifies asymmetric groups for which only one radius may not be representative of its size. Therefore, we explored different definitions of group radius corresponding to the projected Lagrangian radii at 50%, 75%, 90%, and 100%.

Computing the line-of-sight velocity dispersion of groups identified by the MST is not trivial. Indeed groups are in close interaction with their environment and members nearer to the edge are likely to be affected by the surroundings. We address this issue by estimating four different velocity dispersions corresponding to the stars lying within the four Lagrangian radii computed above. We also chose to compute the velocity dispersion using the biweight scale estimator (Beers et al. 1990) which is more robust than the standard deviation when the distribution contains outliers.

4. Assessing projection bias

4.1. Real groups

We thus obtain four different sets containing $16 \times 96 = 1536$ different estimates of the dynamical masses of real groups. These are plotted in Fig. 5. The distributions of all these estimates for each group are summarised as box-plots, where the median is shown as an orange vertical tick mark; the 16th and 84th percentiles by the box edges; and the extrema by the whiskers. The slope of the correlation between the dynamical and real mass in each panel matches the corresponding value of $\eta$ for each radius. We compute this slope by a least-squares linear regression fit in each case. We see a clear correlation present at all radii, with a constant relative uncertainty of $\delta \eta/\eta \approx 0.12$, an indication that the correlation still holds even when including stars at the group edges.
Fig. 5. Correlation between the true and dynamical mass of real groups. Each panel shows different chosen radii for the dynamical mass estimate. All possible values along different projecting angles for the same group are shown in a box-plot: the orange vertical tick marks represent the median of the distribution; the edge of the box, the 16th and 84th percentiles (such that 68% of the data are inside the box), and the horizontal bars correspond to the total width of the full distribution. The red lines are the least square fits on the data giving the values of $\eta$ corresponding to each radius.

Fig. 6. Correlation between the true and dynamical masses of groups identified in projection represented as a 2D histogram. The black line shows the expectation constrained from real 3D groups (see Fig. 5). Different shaded areas show the fraction of well-estimated group masses within an error of 50% and 100%.

4.2. Projected groups

We focus now on the projected groups. We re-use the 96 viewing angles of the whole region computed in Sect. 3.4 to reach a similar number of mass estimates. As changing the line-of-sight will result in a different identification of projected groups, we re-compute the MST in each projection. Small variations in the number of groups identified in each projection lead to a different total number of projected groups of 1425. Their dynamical masses were estimated with the corresponding $\eta$ factors constrained above (Sect. 3.4). The correlation with their real masses is plotted in Fig. 6 as a two-dimensional histogram. The black line shows the correlation derived from real groups. However, all mass estimates are shifted to lower values, falling to the left of the one-to-one relation on the figure. This highlights the fact that the mass of a group is underestimated when viewed in projection, irrespective of its true mass. The trend is not different from one panel to another, confirming that it is not sensitive to the choice of the radius. Globally, the deficit is greater than 50% for more than half of the groups, reaching 100% for a quarter of them. We attribute this systematic error to the misidentification of clumps due to projection effects. As all radii are affected, the centre and the outskirts of projected groups are similarly impacted.

To further investigate the reason for this deviation, we also compared radii and velocity dispersions of real and projected groups with similar masses. We divided both sets into three bins in terms of mass: [15; 35] $M_\odot$, [35; 100] $M_\odot$ and [100; 300] $M_\odot$. The results corresponding to the 90% Lagrangian radii are plotted in Fig. 7, but other radii give similar trends. We take a statistical approach to explore differences between real and projected groups. The distributions within each mass bin are represented by box plots of different colours: black for real groups and blue for projected groups. We recover on the left panel the systematic error in dynamical mass between real and projected groups (previously seen on Fig. 6). The two other panels show the respective distributions of radii and velocity dispersions used to compute the dynamical mass. The properties of projected groups in a given mass bin are statistically lower than those of real groups. Moreover, the trend is more pronounced for the most massive groups. For the less massive groups, their Lagrangian radii are globally comparable whereas their velocity dispersions are systematically about 20% lower. We note here that this is not the case when choosing only the stars lying in the 50% or 75% Lagrangian radii where Poissonian fluctuations can increase the difference up to $\approx 30\%$. For groups more massive than 100 $M_\odot$, both radii and velocity dispersions are equally shifted by about 30%, independently of the chosen radius.

In summary, projection effects lead to significant underestimation of both the size and velocity dispersion of projected groups. Only the radii of the less massive groups are nearly not affected. Some may find it surprising that the velocity dispersion is lowered in projected groups where some stars are not part of any clumps. However, we must bear in mind that these
stars are in the same region, and therefore they are likely to have a velocity close to the mean value (of ≈0 km s$^{-1}$ in our case, see Sect. 5.1), which is the reason for the lower velocity dispersion in projected groups.

### 4.3. Incompleteness

Projection effects are always present in astronomical observations where spherical symmetry is a valid ansatz. This eases comparison with theoretical models. However, this assumption is not justified for young systems. We indeed show that a lack of precise information in the line of sight can introduce systematic biases in the clump properties.

Another common bias when studying young stellar systems arises from incompleteness of the target populations. This also affects particularly star forming regions where extinction can be significant. We may estimate the importance of the completeness of the sample in comparison with that of the morphological projection biases that we have been discussing so far. At first order, the faintest sources are also the least massive ones, and so we apply different mass cuts to the set of projected groups (at 0.3 $M_\odot$, 0.5 $M_\odot$ and 1 $M_\odot$). Again, we estimated the properties of the resulting groups on the different lines of sight. Figure 8 shows the resulting dynamical mass distribution within the three mass bins defined earlier in Fig. 7. Distributions of real groups and complete projected groups from Fig. 7 are also plotted for comparison. We observe that the distribution of dynamical mass estimates is progressively shifted to smaller values when incompleteness increases. This trend is expected, because the more massive stars selected are segregated in space over a smaller volume (Dorval et al. 2016), while their velocity dispersion will also be lower due to star–star interactions. As incompleteness of the sample will always increase the scatter owing to lower number statistics, dynamical mass distributions of incomplete groups show greater dispersion.

This analysis is just the first step in a longer process, as we know that the problem of incompleteness is complex. Detection limits of observations is wavelength dependant and extinction is never constant inside the same star forming regions. Indeed, dust clouds also harbour filamentary structures in interaction with newly born stars and dramatically modify the aspects of these clusters. Other important additions are the stellar photometry and interstellar reddening, two quantities affecting the sampling of stars with opposite results. Indeed, the most massive
stars are the brightest but are also likely to be the most embedded (Motte et al. 2018). A self-consistent simulation including hydrodynamics would be needed to more accurately explore these aspects.

5. Discussion

5.1. Decontamination

We recall that the stars contaminating the set of projected groups are stars from the same region, separated only by a few parsecs and sharing the same global dynamical state. Therefore, it can be difficult to distinguish between contaminants and group members based on their kinematics alone. We ask if Gaia DR2 proper motions can separate two groups seen in projection using their individual proper motions. If we use a reference distance to Orion of 400 pc (Kounkel et al. 2018), the highest accuracy of Gaia DR2 proper motions is 0.1 km s\(^{-1}\) at \(M_\odot = 13\) but only reaches 1 km s\(^{-1}\) at \(M_\odot = 18\). As Gaia EDR3 will improve this value by a factor of two, we can expect to distinguish between two groups separated by a systematic motion of more than 0.5 km s\(^{-1}\).

Figure 9 shows a one-dimensional position–velocity plot of stars in real (3D) groups. Each point is colour-coded as in Fig. 3. Field stars are shown in light grey. The filled circles are the mean values for each group and the error-bars represent the standard deviation, which is an estimate of the typical internal motion of the clumps. An indication of the relative motions between these groups is given by the standard deviation of these mean values, which is \(\approx 0.4\) km s\(^{-1}\). This is of the same order as the internal motion, which is \(\approx 0.5\) km s\(^{-1}\). We conclude that the majority of real groups cannot be differentiated. We find only one instance where two out of sixteen groups are separated by \(\approx 2\) km s\(^{-1}\) which is within the Gaia detection limit. This is by construction a feature brought by our GDF method, because we did not introduce large-scale motion in our fragmentation method. Such large-scale modes can be included in a future study.

5.2. Varying the total number of stars in the region

Although the reference set of 15 000 stars we previously studied allows us to explore clumps of different membership and density, the large projected density of \(\approx 500\) stars pc\(^{-2}\) can have an impact on the level of contamination of these clumps. Moreover, such clumpy configurations are not always seen in star forming regions. However, it is clear that none of the star forming regions are perfectly isolated (Kuhn et al. 2014). The local environment of a particular region, even if it is not as structured as in our reference model, can still introduce some biases when inferring its properties. To probe such conditions, we built a GDF model with only 1000 stars and repeated the analysis. The sub-selection method with the 8DP algorithm (Sect. 2.3) extracts a sample of 765 stars for a surface density of 50 stars pc\(^{-2}\). This new model is, as expected, less structured: only one major overdensity developed at the centre of the region (see upper panel of Fig. 10). We therefore focus on this single clump detected by the MST. However, some structures exist in its environment that may contaminate it when seen in projection. We performed the estimation of the dynamical mass of this single group as in Sect. 3.4. We used the values of \(\eta\) constrained previously in Sect. 3.4. We also identify groups in projection for the same 96 lines of sight\(^4\) and estimate their dynamical mass too. Finally we compare the distribution of both estimations. The distributions corresponding to the 75% Lagrangian radii can be seen in the bottom panel of Fig. 10. Other radii show similar behaviours. The true mass of the group is marked as the red line for reference. The results are similar to those shown in Fig. 8: the dynamical mass of the projected group is systematically lower than that of the real group. Therefore, even the smaller number of sub-structures in this model can still lead to inaccurate estimation of clump properties. Second, although the value of \(\eta\) was not calibrated on this model, the dynamical mass is well retrieved in 3D. Our overall conclusions are therefore not sensitive to the precise surface density at least from 50 stars pc\(^{-2}\) to 500 stars pc\(^{-2}\).

5.3. Clump-finding algorithm

Our study specifically aims to assess the bias introduced by projection effects within a star forming region. We show that projection effects systematically lower the spatial and kinematic properties of clumps. However, the amplitude of this shift is difficult to quantify. The variation that we estimate to range from 10 to 30% is due to the intrinsic nature of projection bias, which depends on the shape and orientation of a particular region. It is also linked to the method we choose.

However, most clump-finding algorithms also use projected spatial coordinates. For instance Joncour et al. (2018) proposed a method to calibrate the DBSCAN algorithm using a statistical approach. The DBSCAN is a close alternative to the MST. These latter authors exploit the nearest-neighbour statistics of a 2D Poissonian distribution to compute the parameters of the DBSCAN. This allows them to select only projected overdensities at three-sigma level over random expectation. Nevertheless, this method is most suitable for small-scale structures of approximately ten members, where contamination in the line of sight is weak. For bigger clumps, like those that we identified in the present study, projection effects are more significant. Therefore, we may expect that such a method will lead to similar results to the MST approach adopted here.

\(^4\) We note here that the MST identifies sometimes more than one group in projection. In such cases, we only retain the most massive one.
Fig. 10. Upper panel: sub-sample extracted from a GDF model of 1000 stars with the method of Sect. 2.3. Only one major group is identified in 3D by the MST (red dots). Lower panel: distributions of the dynamical mass estimated on different projections of the main group identified by the MST in 3D (black line) and in projection (blue line). The true mass is marked as the vertical red line.

A step forward would be to build a set of GDF models reproducing configurations of a wide range in density, and train a machine-learning algorithm on this sample to bridge the 3D identifications to 2D projections with a significance estimator, similarly to what was developed by Joncour et al. (2018) for DBSCAN. We show here that all groups show comparable projection biases, with a trend of increasing amplitude with group mass. This suggests that a data set of models with reasonably small groups –of up to 1000 stars– should still yield useful statistics while remaining manageable in terms of volume. Further work in that direction is underway.

5.4. The mass-to-light ratio $\eta$

A secondary result emerging from this study is the value of the mass-to-light ratio $\eta$ linking the true and dynamical masses of real groups (see Sect. 3.4). The value $\eta \sim 10$ is often chosen to match a wide range of spherical King-Mitchie models (Spitzer 1987; Mengel et al. 2002). However, Fleck et al. (2006) already showed that $\eta$ varies tremendously through the lifetime of a cluster, mostly as a result of mass segregation.

The value $\eta \approx 10$ is about a factor three greater than our evaluation of $\approx 3.4$ for real groups. Previous works (see e.g.,

Portegies Zwart et al. 2010; Parker & Wright 2016) predicted that low values of $\eta$ could be a signature property of young systems, one related to their state of equilibrium. As nothing suggests that real groups are in virial equilibrium, such a low value of $\eta$ could be an indication of expansion. We rule out this explanation by computing the radial velocities of stars in real groups from their respective centres of mass. The median for each group is plotted in Fig. 11. It shows that real groups are in a quasi-steady state, with $v_r \approx 0$ km s$^{-1}$. This is perhaps surprising, because they are in close interaction with their environment, for instance through the tidal field of neighbouring groups and fly-by stars. However, it must be borne in mind that these configurations are a snapshot taken after only $t \approx 0.5$ Myr. The age of the system is of the same order as the dynamical crossing time for groups, when little internal kinetic energy diffusion has had time to drive expansion.

Precise determination of $\eta$ should help observers to put further observational constraints on the dynamical state of sub-clusters in star forming regions. For instance Kuhn et al. (2019) recently computed the virial-expected velocity dispersion of 19 young clusters. A lack of constraints on the value of $\eta$ has prevented confirmation of the equilibrium dynamical state of these systems. Assuming a value of 10 lead Kuhn et al. (2019) to conclude that all of these clusters were unbound, although their Gaia proper motions did not show clear signs of expansion. Using a reduced value of 5, closer to our evaluation, would reconcile these contradictory results. We stress that the systems that we have analysed, which are of linear scale $\approx 0.5$ pc or less, are small compared to those of Kuhn et al. (2019). To make a more meaningful comparison with their survey would require that we develop models of a full-size $\approx 100$ pc region, with disc-shearing and the vertical disc structure of the Milky Way added to the GDF modelling of Sect. 2. We hope to report on these aspects in a future contribution.

6. Conclusions

In the present study, we use GDF models to self-consistently reproduce a fragmented distribution of stars to assess the systematic bias introduced by an imprecise identification of stellar clumps in projection compared to an ideal one in 3D. To this end,
we performed a statistical comparison between the properties of stellar over-densities (of membership \(N_{\text{stars}} > 50\)) identified in 3D and in projection by a generic MST algorithm within a single star forming region of \(\approx 4\) pc in width\(^5\). Our main results can be summarised as follows:

1. We highlight that the dynamical mass of clumps identified in projection is systematically underestimated compared to the ideal 3D identification. This systematic error is greater than 50% in about half of the cases and can reach up to 100% in a quarter of them. This is due to the incorrect selection of the clump-finding algorithm when dealing only with projected coordinates in such fragmented regions.

2. This projection bias impacts both radius and velocity dispersion estimates of projected groups. Eliminating potential outliers at the edges of the groups identified by the MST did not lead to any improvements.

3. We notice a trend ranging from the properties of less massive \((M < 100 M_\odot)\) groups, which are less affected or even not at all, to those of the most massive groups \((M > 100 M_\odot)\), which are more systematically affected. For these latter, radii and velocity dispersions are statistically 30% lower.

4. As the projection effect is not the only bias in star forming regions, we also considered simple prescriptions to account for incompleteness in the observations. We show that sample incompleteness increases the systematic error. However, its impact is of a different nature and can be seen as a blurring effect. For example, the most massive groups are almost unaffected since they still contain a sufficient number of massive members for them to be characterised.

5. We conclude that projection effects are the main limitation in estimating properties of clumps identified within a single fragmented region with no or insufficiently accurate distance estimates. For most nearby star forming regions, the best Gaia parallaxes have uncertainties of a few percent. For these distant regions, that is, at more than 100 pc, this prevents any clump-finding algorithm from properly defining clumps of less than a few parsecs in size. Accurate identification of such clumps is a key challenge in better constraining the processes of star formation. This also has major implications for predicting the future of these young systems in bound clusters or unbound associations.

6. We also show that GDF models offer an efficient method to initialise N-body simulations of young clusters. With this method, we are able to explore the structures built by gravity alone in more detail in order to better understand the role of gravity compared to the many processes at play in star forming regions.

Acknowledgements. We thank the referee for the constructive remarks which led to improve the quality of the paper. Timothée Roland also acknowledges Paolo Bianchin, Caroline Bot, Joe Lewis and Jonathan Chardin for their helpful comments and suggestions. This work has used the AMUSE framework (https://github.com/amusecode/amuse) (Portegies Zwart & McMillan 2018; Portegies Zwart et al. 2009, 2013; Pelupessy et al. 2013) and the Python programming language with the following packages: matplotlib (Hunter 2007), NumPy (Harris et al. 2020), SciPy (Virtanen et al. 2020) and Astropy (Astropy Collaboration 2013, 2018).