DEFINITION OF INVARIANTS IN 3-D

Application: Study of the number of jets in e+e- events

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Abstract. We define invariants for 3D objects with a spherical symmetry. These new invariants are used to study the number of jets in e'e events.

1-INTRODUCTION

In pattern recognition, some 2D invariants were used to solve some rotation invariant problems 1.

But in e^te⁻ events, the jets have a spherical 3D symmetry. The usual method to tag the number of jets is the clusterization using classical algorithms . An attempt to use a neural network was done by Jousset³ using an Hopfield neural network.

In this paper we propose a set of 3D invariants which can be used to study the number of jets in e'e events.

2-INVARIANTS IN 3D ROTATION

The angles used in 3D rotation are ϑ and ϕ ; we know the spherical orthogonal functions $Y_{1m}(\vartheta,\phi)^3$.

A function $f(\vartheta,\phi)$ can be developped using $Y_{1m}(\vartheta,\phi)$ functions. $f(\vartheta,\phi) = \sum_{1} \sum_{m}^{\alpha} r_{1m} Y_{1m}^{*}(\vartheta,\phi) .$

If the axis are rotated with α, β, γ Euler angles the rotation angles become ϑ ' and ϕ '. The new development is $f(\vartheta,\phi) = \sum_{1} \sum_{m} \alpha'_{1m} Y_{1m}^{\star}(\vartheta',\phi').$

$$f(\vartheta,\phi) = \sum_{1} \sum_{m} \alpha' 1m Y_{1m}^{\star}(\vartheta',\phi').$$

But we know a relation between
$$\vartheta, \phi$$
 and ϑ', ϕ' angles³.
$$Y_{1m}(\vartheta', \phi') = \sum_{m'} \mathcal{D}_{m'm}^{1}(\alpha, \beta, \gamma) Y_{1m'}(\vartheta, \phi),$$

where the Ø functions are the usual orthogonal functions with Euler angles.

The relation between α' and α is then:

$$\alpha'_{1m} = \sum_{m''} \mathcal{D}_{m''m}^{1}(\alpha, \beta, \gamma) \quad \alpha_{1m''}.$$

Using the orthogonal relation³

$$\sum_{m} \mathcal{D}_{m''m}^{1*}(\alpha,\beta,\gamma) \mathcal{D}_{m'm}^{1}(\alpha,\beta,\gamma) = \delta_{m'm''},$$

we see that the combination of the α values

$$\beta(1) = \sum_{m} \alpha_{1m} \alpha_{1m}^{\star}$$

is invariant for a 3D rotation.

The α parameters are computed with the relation

$$\alpha_{lm} = \int f(\vartheta, \phi) Y_{lm}(\vartheta, \phi) d\Omega,$$

 $\alpha_{\mbox{\it lm}} = \int \mbox{ } f(\vartheta,\phi) \mbox{ } Y_{\mbox{\it lm}}(\vartheta,\phi) \mbox{ } d\Omega,$ using the associated Legendre functions $P_{\mbox{\it m}}^{\mbox{\it l}}(\cos\vartheta)$ we write for the α coefficients:

$$\alpha_{1m} = (-)^m \left[\frac{(2\,l+1)\,(\,l-m)\,!}{4\,\pi\,\,(\,l+m)\,!} \right] \int \, P_m^{\,l}(\cos\vartheta) \, e^{i\,m\varphi} \,\, f(\vartheta,\varphi) \,\, d\Omega \ .$$
 The contributions to $\beta(\,l)$ of opposite m values are identical.

3-SIMULATION OF 3 CLASSES

We have simulated 3 classes of different simple objects with dots on a sphere.

Classe 1:2 dots at $\vartheta_1=0, \phi_1=0$ and $\vartheta_2=\pi, \phi_2=0$.

Classe 2:3 dots at $\vartheta_1=0, \phi_1=0$; $\vartheta_2=2\pi/3, \phi_2=0$ and $\vartheta_3=2\pi/3, \phi_3=\pi$.

Classe 3:4 dots at $\vartheta_1=0, \phi_1=0$; $\vartheta_2=\pi, \phi_2=0$;

$$\vartheta_3 = \pi/2$$
, $\phi_3 = 0$; $\vartheta_4 = \pi/2$, $\phi_4 = \pi$.

We have verified the invariance of $\beta(1)$ values with random Euler angles. When we introduice a noise in the positions of the dots,the $\beta(0)$ value is discriminating for the classes,because

$$\beta(0) = \frac{1}{4\pi} (\sum_{\text{dots}} P_0^0)^2$$
,

this value is independant of the noise.

4-THE NUMBER OF JETS IN e⁺e⁻ EVENTS

In LEP detectors, the tracks of an hadronic event are given by the momentum p_i , the ϑ_i and ϕ_i angular positions.

We choose as f function the following relation:

$$f(\vartheta,\phi) = \sum_{i \text{ tracks}} p_i \delta(\cos\vartheta - \cos\vartheta_i) \delta(\phi - \phi_i)$$

then

$$\alpha_{1m} = (-)^m \left[\frac{(2 - \frac{1}{4\pi}) \cdot (\frac{1}{1+m}) \cdot (\frac{1}{1-m})}{(1+m)!} \right] \sum_{i \text{ tracks}} p_i P_m^{1} (\cos \theta_i) e^{i m \phi_i}.$$

We have generated 2,3 and n jets events with the ALEPH Monte-Carlo simulation. The jets were clustered with the JADE algorithm using ycut=(6/E)**2.

The beta variables are interesting to study the shape of an e⁺e⁻ event, but other shape variables have already been used in high energy physics⁴,⁵. The sphericity product, the aplanarity, Fox-Wolfram coefficients can be used.

In our study,we have used 23 variables:sphericity product,aplanarity,Fox-Wolfram coefficients H40 and H50.A F-test method⁵ applied to these variables,showed that their discriminating power for the study of the jets is important.To these 4 variables we have added 19 β_i coefficienits:i=0..18.

We have feeded a (23-23-8-3) MLP neural network: the inputs are the 23 variables, we use 2 hidden layers, the 3 outputs are the 3 classes: 2 jets events, 3 jets events, n jets events.

The learning was done with a set of 3*2400 events. The test was done on a set of 73376 events: 48948 2 jets events, 21385 3 jets events, 3033 n jets events.

In the test,85.3% of the events were correcty classified.

The classification given by the MLP network gives:

The purity of a 2 jets sample is 95.9%,

The purity of a 3 jets sample is 75.3%,

The purity of a n jets sample is 41.6%.

The percentage of true 2 jets tagged as 2 jets is 89.6%,

The percentage of true 3 jets tagged as 3 jets is 75.4%,

The percentage of true n jets tagged as n jets is 85.0%.

In figure 1 we give the outputs of the neurones of the 4th layer. In figure 2, we give the curves of purity/efficiency⁴ for the 3 classes of the problem.

5-CONCLUSION

We have computed a new family of 3D invariants. We have given some results of a study of the number of jets in e^+e^- events.

The study of the jets can be improved, because we have supposed that the JADE algorithm is perfect.

6-AKNOWLEDGMENTS

The simulation in high energy physics, were done with ALEPH full Monte-Carlo simulations. I would like to thank the physicists from ALEPH for the quality of the software and for their constant support.

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Figure captions

Figure 1

Outputs of the MLP neural network

1-2 jets events

2-3 jets events

3-n jets events

4-not 2 jets events

5-not 3 jets events

6-not n jets events

Figure 2

Purity versus efficiency

stars: 2 jets events lozenge:3 jets events circle: n jets events

Figure 1

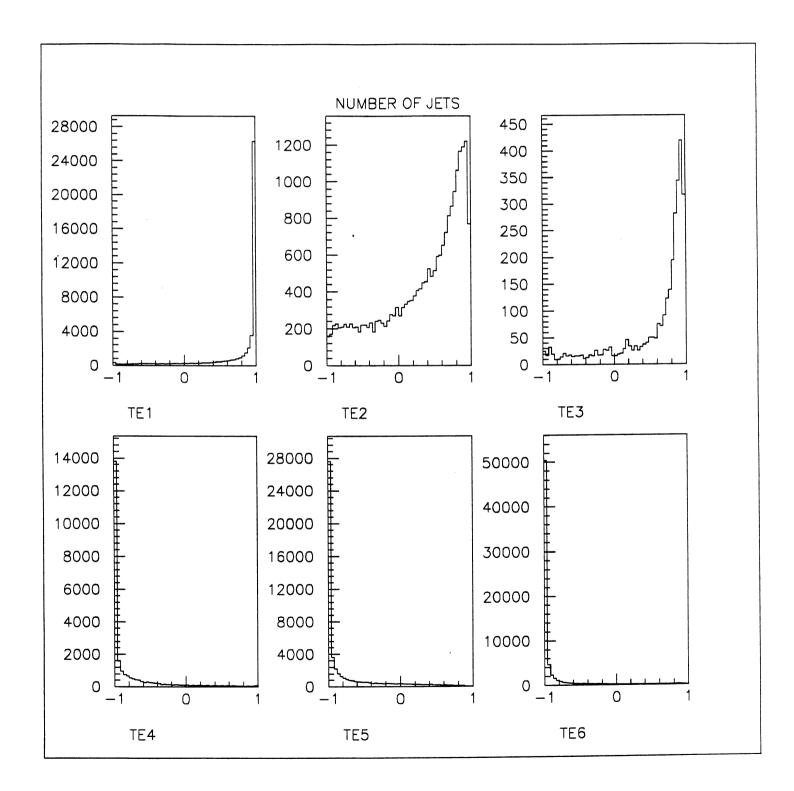


Figure 2

