

# The Bhattacharyya Measure

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## 1 Introduction

An important problem in computer vision is measuring the dissimilarity between distributions of features, such as colour and texture (cf. (Rubner, Puzicha, Tomasi & Buhmann, 2001)). The focus of this note is on the *Bhattacharyya measure* and its derivatives. For a discussion of the statistical foundations of the Bhattacharyya measure, the reader is referred to (Aherne, Thacker & Rockett, 1997).

## 2 Bhattacharyya measure

Let  $p(i)$  and  $p'(i)$  represent two multinomial populations, each consisting of  $N$  classes with respective probabilities  $p(i = 1), \dots, p(i = N)$  and  $p'(i = 1), \dots, p'(i = N)$ . Since  $p(i)$  and  $p'(i)$  represent probability distributions,  $\sum_{i=1}^N p(i) = \sum_{i=1}^N p'(i) = 1$ . The Bhattacharyya measure (Bhattacharyya, 1943) (or coefficient) is a divergence-type measure between distributions, defined as,

$$\rho(p, p') = \sum_{i=1}^N \sqrt{p(i)p'(i)}. \quad (1)$$

The Bhattacharyya measure has a simple geometric interpretation as the cosine of the angle between the  $N$ -dimensional vectors  $(\sqrt{p(1)}, \dots, \sqrt{p(N)})^\top$  and  $(\sqrt{p'(1)}, \dots, \sqrt{p'(N)})^\top$ . Thus, if the two distributions are identical, we have:

$$\cos(\theta) = \sum_{i=1}^N \sqrt{p(i)p'(i)} = \sum_{i=1}^N \sqrt{p(i)p(i)} = \sum_{i=1}^N p(i) = 1, \quad (2)$$

and consequently  $\theta = 0$ . Furthermore, based on *Jensen's inequality* (Cover & Thomas, 1991), we have,

$$0 \leq \rho(p, p') = \sum_{i=1}^N \sqrt{p(i)p'(i)} = \sum_{i=1}^N p(i) \sqrt{\frac{p'(i)}{p(i)}} \leq \sqrt{\sum_{i=1}^N p'(i)} = 1. \quad (3)$$

A potentially undesirable property of the coefficient is that it does not impose a *metric* structure since it violates at least one of the distance metric axioms (Fukunaga, 1990). In (Comaniciu, Ramesh & Meer, 2003), the authors propose the following modification of the Bhattacharyya coefficient that does indeed represent a metric distance between distributions:

$$d(p, p') = \sqrt{1 - \rho(p, p')}, \quad (4)$$

where  $\rho(\cdot, \cdot)$  denotes the Bhattacharyya coefficient (1). For the proof that this distance is indeed a metric (i.e., obeys all of the metric axioms), see Appendix in (Comaniciu, Ramesh & Meer, 2003).

Next, let us consider a related measure, the *Hellinger discrimination* (Hellinger, 1909) (also known as the *Matusita* measure (Matusita, 1955)). This measure defines the distance between two probability distributions, as:

$$\sum_{i=1}^N \left( \sqrt{p(i)} - \sqrt{p'(i)} \right)^2. \quad (5)$$

This measure is related to the Bhattacharyya coefficient (1),  $\rho(\cdot, \cdot)$ , and distance (4),  $d(\cdot, \cdot)$ , by:

$$\sum_{i=1}^N \left( \sqrt{p(i)} - \sqrt{p'(i)} \right)^2 \quad (6)$$

$$= \sum_{i=1}^N \sqrt{p(i)}\sqrt{p(i)} - 2 \sum_{i=1}^N \sqrt{p(i)}\sqrt{p'(i)} + \sum_{i=1}^N \sqrt{p'(i)}\sqrt{p'(i)} \quad (7)$$

$$= \sum_{i=1}^N p(i) - 2 \sum_{i=1}^N \sqrt{p(i)}\sqrt{p'(i)} + \sum_{i=1}^N p'(i) \quad (8)$$

$$= 2 - 2 \sum_{i=1}^N \sqrt{p(i)}\sqrt{p'(i)} \quad (9)$$

$$= 2 - 2\rho(p, p') \quad (10)$$

$$= 2(1 - \rho(p, p')) \quad (11)$$

$$= 2d(p, p')^2. \quad (12)$$

Finally, let us turn our attention to the relationship between the the Bhattacharyya coefficient (1) and the *chi-square* ( $\chi^2$ ) measure. The chi-square measure is used to provide a measure of similarity between two distributions (cf. (Leung & Malik, 2001)):

$$\chi^2(p, p') = \frac{1}{2} \sum_{i=1}^N \frac{(p(i) - p'(i))^2}{p(i) + p'(i)}. \quad (13)$$

In (Aherne, Thacker & Rockett, 1997) it is shown that the Bhattacharyya coefficient (1) approximates the  $\chi^2$ -measure (13), while avoiding the singularity problem that occurs when comparing instances of the distributions that are both zero.

## References

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