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Shapes classification of dust deposition using fuzzy kernel-based approaches

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ABSTRACT

Dust deposition and pollution are relevant issues in indoor environments, especially concerning human health and conservation of things and works. In this framework, several tools have been proposed in the last years in order to analyze dust deposition and extract useful information for addressing the phenomenon. In this paper, a novel approach for dust analysis and classification is proposed, employing machine learning and fuzzy logic to set up a simple and actual tool. The proposed approach is tested and compared with other already introduced similar techniques, in order to evaluate its performance.

1. Introduction

Airborne pollutants may generate the occurrence of health hazards, as well as damage to things and works. In particular, they can arise in the form of vapors and gases or as aerosols. The latter consists of a mixture of particles (e.g., dusts, smokes, and fumes) suspended in a gaseous medium. Among all this agent, dust is a relevant source of disease for humans and things. In order to optimally address pollution effects, the first and fundamental stage is the understanding of the dust sources, of its accumulation phenomenon and of the exposure conditions. For this purpose, the main features that must be identified regarding the elements of dust are the size and the shape (meaningful in terms of particles or fibers) that firstly allow to design suitable tasks to address this issue (e.g., the selection of the best suited filtering unit). In this paper, this analysis is performed automatically, presenting a new method for obtaining information regarding the size and shape of the elements of dust.

Dust monitoring can be generally carried out according to two different methods:

1. the sampling with further lab analysis, which allows obtaining detailed and specific information about dust samples requiring the use of complex and generally expensive instrumentation and
2. the real-time measurement with direct reading instrumentation, which are a best-effort technique for a quick screening of environments during the addressing start-up stage.

In the dust analysis framework, computational intelligence can aim at implementing low-cost tools for solving dust classification and characterization problems, in order to extract useful information to design addressing approaches or even to suitably perform dust sampling for further detailed lab analysis. Some approaches based on computational intelligence for dust analysis were already presented, especially showing interesting performances

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as well as valuable savings in terms of cost and instrumentation complexity [1,2]. Among all these approaches, pattern recognition is optimally used in many fields [3–9] because is considered as an efficient method for analyzing either small or big amounts of data, i.e., for grouping and dividing objects by using some measures of similarity or dissimilarity on the basis of a suited number of features representing data [10].

In this paper, a new dust classification and analysis approach based on image processing, machine learning and fuzzy logic is presented. This results in a direct reading approach in the form of a portable tool, aiming at simple and ubiquitous set-up. The proposed approach is able to extract information about size (in terms of area) and shape of each dust element, distinguishing particle from fiber elements. Such information generally allows correctly understanding and modeling the dust deposition and, hence, to better address the related issues. Respect to the state-of-the-art system, the proposed approach allows obtaining information about dust using a simple and low-cost tool, able to carry out direct and real-time investigation. Namely, it does not require onerous methodologies (such as chemical and physical analysis) or expensive instrumentations. Finally, it allows obtaining an accurate classification in terms of misclassified elements with respect to other similar approaches (as detailed in Section 6).

The paper is organized as in the following. Section 2 describes the sensing apparatus and the data preprocessing stage. Section 3 presents the selected features and the features extraction stage. Section 4 shows the metrics employed in the data space modeling. Section 5 presents the classification stage, which occurs according two different techniques relying on a convex-hull evaluation (described in Section 5.1) and on a totally geometrical unconstrained approach (described in Section 5.2). Finally, tests and results of the proposed classifiers are reported in Section 6, showing their good performances.

2. Sensing and preprocessing

The dust classification approach proposed in this paper relies on the dust sensing system presented in [11]. It consists of a high-definition (HD) CMOS imaging sensor deprived of the optical section (lens and other optical apparatuses) as to allow the direct dust deposition on the CMOS surface. The sensor axis slopes of 45° with respect to the ground plane allowing dust gradually falls because of the gravity and so a minimized dust overlapping. In order to maximize contrast and focus, a hi-power led lamp perpendicularly lights up the sensing surface. Thanks to this simple setup, the sensing apparatus is able to acquire dust samples shadows as showed in Fig. 1. The sensing apparatus acquires frame according to a regular time interval, customizable by the user through an ad-hoc developed interface. A suitable preprocessing stage extracts individual dust elements from each frame, applying standard image preprocessing tools as denoising, filtering, equalization, and so on. Assume in the following that each dust shadows was processed as a binary image, extracted by finding the *connected components* [12] in the overall frame.

Fig. 1. A dust shadows image captured by using the sensing apparatus based on the HD CMOS optical sensor.

Based on the dust shadows, the proposed approach is able to return different meaningful information about the dust deposition:

1. size information, as the sum of the image pixels related to the pixel area in μm;
2. distribution information about the deposition phenomenon, directly or indirectly inferable to the dust shadows set (such as accumulation speed, coverage ratio – occupied surface versus free surface –, size spectrum and so on);
3. shape information, namely distinguishing between particulate and fibers, thanks to the following discussed classification approach.

3. Features extraction

A crucial task in classification is the selection of a suitable number of features representing the data. In [13] various methods using suited pattern recognition approaches are illustrated in order to establish feature ranking, selection and extraction, including the dimensionality reduction that often is a critical matter for the computational cost.

In order to compose the dataset for classification, each dust element has to be characterized in terms of data features, which can then be given as input for the classifier. Let $\mathbf{I}$ be a matrix representing a dust shadow binary image composed by S pixels. The data characterization used in the present case relies on a three-features model composed by the shadow boundary length, the isoperimetric index and the varimax norm, which are briefly summarized in the following:

1. Length b of the shadow boundary, evaluated using the Moore neighbor tracing algorithm adopting Jacob's stopping criteria [14]. This method returns a binary image $\mathbf{I}_b$ containing the S pixels of the original image $\mathbf{I}$, where only the boundary pixels q_i are set to one and the others are set to zero. Hence, b can be calculated as:

$$b = \sum_{i=0}^{S-1} q_i. \tag{1}$$

2. *Isoperimetric index* g resulting by the isoperimetric theorem [15]: