



Lasers in Manufacturing Conference 2017

# Monitoring of powder flow dynamic behavior in LMD processes by high speed imaging

J.N. Montero<sup>a</sup>, A. Rodriguez<sup>a</sup>, J.M. Amado<sup>a</sup>, M.J. Tobar<sup>a</sup>, A. Yañez<sup>a,\*</sup>

<sup>a</sup>University of ACoruña, Centro de Investigacións Tecnolóxicas. Campus de Esteiro, s/n , Ferrol, 15403, Spain

#### **Abstract**

In laser metal deposition processes the interaction between the powder particles and the melt pool has a direct effect over the bead quality and part dimensional accuracy. This fact makes important the study of powder beam particle distribution and particle speed to ensure their values are kept under acceptable limits. Those quantities, however, can change with time during the equipment operation or be subjected to perturbations. Dynamic behavior of the solid phase flow is difficult to determine and in most cases it is not studied. To address this issue a monitoring system based on high speed imaging of the powder particles is presented. This monitoring system is able to record changes in the powder mass flow rate and powder distribution by sampling particle crossings in a row of pixels during a fraction of a second. Real time monitoring can be achieved to detect flow perturbations or misalignment of the LMD head.

Keywords: Powder technology; Laser metal deposition; Lase Cladding; Hight-speed monitoring;

#### 1. Introduction

In laser metal deposition processes the interaction between the powder particles and the melt pool has a direct effect over the bead quality and part dimensional accuracy Huan et al., 2012, Pekkarinen et al., 2016. This fact makes important the study of powder beam particle distribution and particle speed to ensure their values are kept under acceptable limits. Those quantities, however, can change with time during the equipment operation or be subjected to perturbations Mann et al., 2013. Dynamic behavior of the solid phase flow is difficult to determine and in most cases it is not studied Yong Yan, 2006, Thayalan and Landers, 1997. To address this issue a monitoring system based on high speed imaging of the powder particles is

<sup>\*</sup> Corresponding author. Tel.: +34-981-337-400; fax: +34-981-337-410. E-mail address: ayanez@udc.es

presented. In the proposed method the measurement of mass flow rate is achieved imaging a particle stream at high frequency with a CMOS camera and laser diode illumination. By detecting particle crossings over a row of pixels in the acquired images an estimation of the number of particles in the flow is calculated. The estimated number of particles, together, with the knowledge of the average particle mass, allows the computation of the mass flow rate. The use of images as the only input makes possible to develop a non invasive system able to determine mass flow rate without disturbing the speed field of solid-gas flows, therefore valid for working inside or outside pipelines and studying jets or other kind of flows that cannot be made pass through a detection chamber. High speed image acquisition makes possible the real time mass flow rate monitoring with milliseconds resolution, the dynamical behavior of the mass flow rate can be observed. For the validation of the methodology and theoretical work a prototype system is presented. In the experimental work stainless steel powder particles of spherical shape with sizes between 44 and 106  $\mu$ m and a Laser Metal Deposition feed system are used. The measurement of mass flow rate is done after the powder particles conveyed by pressurized nitrogen get out of a nozzle and travel across the environment at room temperature.

# 2. Methodology

In two phase solid-fluid flows, the solid phase and its mass appear separated in the form of particles or granules of different sizes and shapes. This discrete nature of the mass flow can be observed by imaging systems and therefore can be used to infer the actual mass. In order to achieve this aim, the proposed idea is to rely only in a measurement of the particles counted in the flow. Pneumatic conveyed particles are expected to move relatively fast with respect to the image space acquired by a sensor, so a particle should not be observed at the same point in two consecutive images; that allows for the implementation of a particle counting method. The particle counting method in its most simple form is performed observing one sensor position through time; when the background value is not recorded a particle is count. Particle count and knowledge of particle mass mean can give, by computing the product between them an estimation of the total mass. This allows the measure of mass flow rate without having to account for particle size or speed. Difficulties arising from the development of a method of particle count are diverse. First, particle mass mean and particle mass variance should be known. Experimentally, sample mean and variance should not be difficult to obtain. It is also possible to deduce this data from particle size distribution provided by powder manufacturers. Second, another source of uncertainty comes from particle speed and shape observed, this complicates the count in some degree. Particles moving too fast can pass without being observed by the sensor, particles moving slow with respect to the image space can be counted multiple times. Finally there is the unavoidable problem of the particle overlap; due to the proximity to each other or their relative position with the sensor two or more particles can appear as one in the images producing undercounting. This problem is common in particle imaging and gets worse as the concentration of solid phase rises Lecuona et al., 2000, N. Damaschke et al., 2002. To tackle those problems, each pixel in the sensor is interpreted as a random variable that can acquire two values, and the sensor measurement is seen as a n dimensional time series where each pixel in the sensor corresponds to one of the n coordinates. Covariograms with temporal and spatial dimensions codifies information about particle size and speed, while the mean values of each coordinate can proportionate information about concentration and concentration distribution. So it seems possible to construct a measurement method that accounts for every mentioned issue only examining the impression that the discretization of solid phase causes in the sensor. In this context, counting particles works as a mapping between an acquired frame and the natural numbers. The behavior of this mapping with time is assumed, under some circumstances, to be a stationary stochastic process and can be modeled; from this model the actual mass flow rate can be inferred.

# 2.1. Model development

The mass flow rate of the solid phase in a two phase flow can be assumed to behave as a moving average and for a small enough lapse of time this average could be considered constant. In that case the number of particles that carry the mass have a mean value and a variance related with the mass flow rate by the particle mass distribution. So, if a sample of particles per unit of volume against time is taken, the measure of particles per sample point will behave as a stationary stochastic process as long as the period sampled is short enough to assume a constant mass flow rate and in that case the resulting time series will be Poisson distributed. The fact that the number of particles per sample is Poisson distributed is widely used in particle image velocimetry Adrian and Westerweel, 2011 for a time series however, sample independence and constant mean must be supposed.

The application of these concepts to the present case is as follows; counting the amount of particles that passes in front of the sensor it is the same as defining a mapping m1 between the sensor outcome and the number of particles presented on and due to particle overlap it is in general not possible. It is only possible to count the amount of particles not overlapped in the sensor, which involves developing another mapping m2. This m2 can be defined as an arbitrary relation between the sensor outcome and the natural numbers. Then, the relation between m1 and m2 (the particle overlap process) becomes another random process G with probability distribution P(m2|m1). Now, if m2 is carefully designed the distribution of G can be calculated for every possible value of m1. In consequence, m2 distribution becomes defined on terms of m1 and G and can be modeled after the marginal probability distribution:

$$P(m2 = k) = \sum_{n} P(m2 = k | m1 = n) P(m1 = n)$$
(1)

Where m1 is poisson distributed. With this is possible to relate m2 mean with m1 mean and as m2 can be sampled calculate m1 mean with relative precision, therefore obtaining the particle flow rate of the lapse surveyed.

What it is left is the calculation of the probability distribution of G, this can be done in different ways, for this case the assumption that the sensor is a line is made. The particles in an ideal linear sensor appear as connected groups of pixels of the same value. For the definition of m2 it is important to assume every particle in the sensor to show the same size. S is taken as the number of pixel a particle must show and should be taken by excess, so the first operation for calculating m2 is to take the sensor outcome and complete the groups of connected pixels by extending the group boundaries until every group has a size equal or greater than S. Then, the groups of connected pixels are counted and used as m2 value. This way, the particle size distribution seen in the sensor does not significantly affect the result, and the particles lost due to overlaps caused by the size added are recovered by the application of the model. G, in this case is defined as the probability of count k connected groups of S pixels of n possible for any value of n and any value of k (k < n) taking into account that those groups are positioned randomly in a sensor of D pixels according to some density function  $\varphi$ . Once computed, the solutions can be used to construct the probability mass distribution of  $G(\varphi,S)$ 

# 2.2. Covariance effect

In the previous section some problems of the counting principle were addressed, like the unknown particle size distribution or the particle image overlap, but there is an important issue for the method proposed to work properly and it is related with the covariances in the outcome of the linear sensor. In the

previous section it was supposed the different sample points to be independent, but it is no like that in a real case. When a particle is seen at a sensor position there exists a considerable probability of detecting it again in the next frame. This phenomenon will depend on speed of the particles, size of the particles and the sensor acquisition frequency. It is important to notice that if frequency is lowered the probability of double detections decrease as well but the probability of losing particles between frames rises. The effect of the covariance over the mass flow rate measurement is not simple and should be modeled thoughtfully. In this paper this issue is not solved but an interesting workaround is proposed and used. The proposed way to approach the problem is to turn off a sensor position after a particle is detected, in that way the same particle cannot be detected in two consecutive measures. It has an important drawback; when particles come one after another some particles are missing, so this idea causes problems when mass flow rates are high. However it allows the measurement to take place and the limit value of measurable mass flow rate can be increased in other ways, like adding optical magnification as an instance.

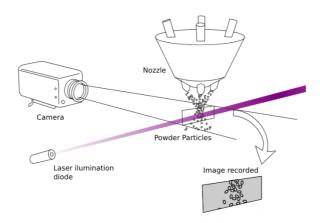


Fig. 1. Monitoring system experimental setup

# 2.3. Model Aplication

As stated before, a probability density function  $\varphi$  is needed to calculate the model. This function corresponds to the concentration distribution of solid phase observed by the sensor, and can be approximated as the normalized mean value of every sensor position during the time lapse surveyed. Once this is done, it is possible to calculate the probability distribution of G that is defined here as  $P_G(n,k)$  for simplicity. The method works as follows; after a sample of n frames from the sensor during a time t is taken, the sample mean of m2 is obtained, together with an approximation of  $\varphi$  and  $P_G$ . With this the mass flow rate is obtained solving for  $\mu$  the equation:

$$\overline{m2} = \sum_{k=1}^{n} \sum_{i=1}^{N} P_G(i,k) \cdot \frac{\mu^i \cdot e^{\mu}}{i!} \cdot k$$
 and computing:

$$q_{m} = \frac{\mu \cdot \mu_{m} \cdot n}{t} \tag{3}$$

Where  $q_m$  is the mass flow rate,  $\mu_m$  is the mean mass per particle and t the total time sampled. The equation 2 comes from calculating the mean of 1 for a finite case, using Poisson distribution for P(m1) and G probability distribution for P(m1|m2). An interesting point is that for a finite case G is invertible so the same result can be obtained by operating:

$$\mu \approx \sum_{k=1}^{n} \sum_{n=1}^{N} P_G^{-1}(n,k) \cdot S_{m2}(k) \cdot k \tag{4}$$

This similar expression, where  $S_{m2}$  is the probability distribution of the sample, acts as a weighted mean and has the advantage of not being dependent of the model of m1, so the conditions for the method to work can be relaxed and calculations can be applied to arbitrary time windows and mass flow change rates.

# 3. Experimental configuration

The laser metal deposition system used in the experimental work is composed of a continuous wave diode pumped Nd:YAG laser (Rofin DY022), a YC30 Precitec cladding head installed on a six axis robot arm and a powder feeding system Sulzer-Metco Twin 10C unit. A CMOS camera (Mikotron EOSENS) connected to a PC by a frame grabber is used to monitor the powder stream. A laser diode with a wavelength of 405 nm and 400mw of power is used for illumination. The camera has a 130 mm zoom lens and it is positioned in front of the laser cladding nozzle, focused in the center of the powder cone as seen in Figure 1. The depth of field is adjusted to maintain in focus the whole powder stream. The exposition time used to obtain a sharp view of the powder particles is around 50  $\mu$ s and the camera acquisition speed is set between 18-20 KHz. For the acquisition of data only a row of pixels is used to simulate a linear image sensor. For correlating the images acquired with the powder feeder disk speed a PCI acquisition card connected to the powder feeder controller is used on the PC. The powder material employed is a gas atomized stainless steel powder (MetcoClad 316L) from Oerlikon. Its particle size varies between 106-44  $\mu$ m and the bulk density used for the steel is taken as 8 g/cm3.

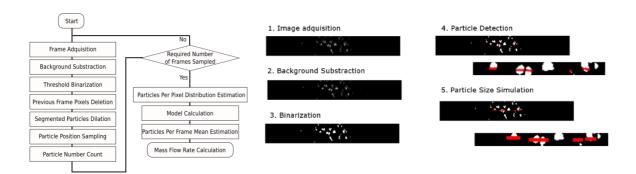
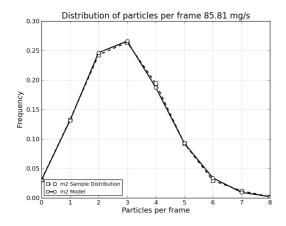


Fig. 2. Flow chart of the mass flow rate calculation process and image processing description

# 3.1. Data acquisition procedure

From the video feed generated by the camera two type of data are acquired, a sample of particles per frame and a sample of particles per pixel. First, for obtaining a sample of particles per frame a simple image processing is performed on each frame. In this process, the background is subtracted and the segmentation of the result is achieved by threshold binarization. This process eliminates the static and dynamic noise. After this the resulting data is processed marked pixels (from a previous step) are set to background level and the center of each group of pixels over the threshold value is located. Once this is done the pixels of each group are marked for their removal in the next image. Finally the extension of group boundaries to a predetermined size is performed for every detected center and the remaining groups are counted. The value obtained is stored as a sample point. At the same time every particle position, the center point of every connected group of pixels measured, is stored during the whole sampling time. The data is used to interpolate a probability density function over the sensor size. The sample distribution of particles and the probability density function obtained are used to perform the calculations. A flow chart of the process and a example of the image segmentation process can be seen in figure 2. Sample times are usually between 5 milliseconds to one tenth of a second and sample rate around 20,000 Hz.



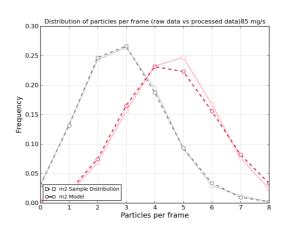


Fig. 3. a) Model fit of processed data

b) Model fit of unprocessed and processed data, p=0.06 p=0.91 respectively

### 4. Results

In the first part of the article expression 1 was proposed for the distribution of the number of particles observable by the camera. For the validation of this model a comparison is made between the theoretical results and the experimental data. The data covers the measurement at constant mass flow rate during one tenth of a second for different output levels. With this data, the sample distribution of m2 is presented against its theoretical distribution. The result of measuring a flow at 5% of the maximum output is shown in figure 3a. When the data is obtained some pixels are eliminated to suppress the negative effect of double detections (described in section 2.2). As an exploratory work some samples were processed with and without this elimination and the results are shown in the figure 3b. The difference of using or not this

operation on the data is clear and it is reflected in the p-values obtained. The results for a mass flow rate at 15% of the maximum output can be seen in the mentioned figure.

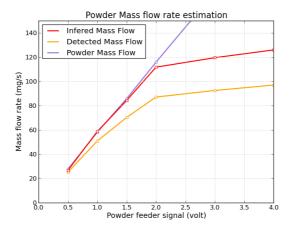


Fig. 4. Mass flow measurement data, monitored mass flow rate vs weighted mass flow rate

# 4.1. Mass flow measure validation

In order to validate how accurately the system can measure mass flow rate it is necessary to compare its results with a measure of the mass flow rate obtained by weighting the particles conveyed. In order to do this, the first required step is to convert the units of measurement from particles per second to mass per second. The manufacturer of the gas atomized stainless steel powder provides information about the particle size mean and variance of the product. For gas atomized powders it is reasonable to assume the particles to be spheres and size distribution to be log-normal Lavernia et al., 1985, so using the bulk density of the material the particle mass distribution can be calculated from the particle size distribution. The second step is to obtain the mass delivered by the LMD feed system under normal working conditions. To achieve this the powder delivery systems is put to work at constant mass flow rate during a minute. The powder conveyed is retrieved and weighted. Different input values are used and weight measures at their respective output levels are taken. A lineal regression is performed over this data; the result correlates the input signal and the mass flow rate. This is a standard procedure for calibration of powder delivery systems. Finally the mass flow rate is measured using the proposed image method. The same mass flow rate parameters as in the weight measurements are used. Samples were taken using 2000 sample points and 100 ms of sampling time. Results are shown in figure 4. In the figure, it is possible to see a point from which the measurement of mass flow rate is no longer possible due to saturation and excess of multiple detections of particles.

It is also possible, as it is mentioned before, seeing changes of mass flow rate in real time. For this end the same process used for validation the mass flow measurement is repeated continuously as the mass flow rate changes, results of this can be seen in figure 5. In this case, 100 frame samples are taken for each data point in 5ms of acquisition time.

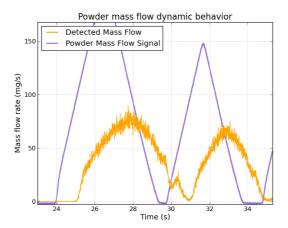


Fig. 5. Real time measurement of mass flow rate.

#### 5. Conclusions

The results obtained from several trials proved the measurement system to be accurate and the particle counting principle in which it is based can be declared valid. The statistical model proposed for the distribution of particles per frame was show to work adequately, and the mass flow rate in the jets produced by the LMD feed system was successfully measured with good time resolution. It is understood that the method proposed can work as a monitoring system in a real world application.

In the tests performed it is possible to appreciate that the system proposed can measure very low flows. In those cases inference of observable particles has almost no effect, being possible to avoid the calculation of the model, that happens because of the low particle overlapping probability at low flows. Despite the good results, limitations have been found; the number of particles per second the system can measure was shown to have an impractical upper bound. Due to the data treatment used to reduce the impact of double detections on the distribution of particles per sample, important data is lost. This lost of data produces a detrimental effect when the amount of particles per second rises, causing the bound. This effect can be mitigated increasing magnification of the optical system which increases the measurable limit of particles per second. Another possibility to confront this problem is to develop a more complete model that includes the sample dependence due to multiple detections of a particle. One aspect of the method, the actual implementation of the computations, was purposely left out of the article. Despite this decision, it is relevant to mention that for real time processing, P<sub>G</sub> (n, k) described in section 2.2, has to be calculated fast. In the implementation used by the authors, this calculation is costly and may hinder performance in some situations. The optimization of this calculation is advisable when the method has to be applied to a real case. Despite this, the presented work offers a new, reliable and flexible way of accurate measuring mass flow rate of pneumatic conveyed particles also able to give an approximation of particle concentration in real time.

# References

- A Lecuona, P A Sosa, P A Rodriguez, R I Zequeira. Volumetric characterization of dispersed two-phase flows by digital image analysis. Meas. Sci. Technol. 2000;11, p 1152.
- Adrian, R. J., Westerweel, J., 2011, Particle Image Velocimetry. Cambridge University Press.
- Hua, T., Fengying, Z., Rujun, W., Jing, C., Weidong, H., 2012. Study of powder flow feed behavior of laser solid forming. Optics and Lasers in Engineering. 50: p. 391
- Lavernia, E., Rai, G., Grant, N.J., Powder Size and Distribution in Ultrasonic Gas Atomization JOM. 1985; 37, p. 22
- Mann, S., Melo, L., Abels, P., 2013, "Measurement of particle density distribution of powder nozzles for laser material deposition." 32nd International Congress on Applications of Lasers & Electro-Optics, ICALEO.
- N. Damaschke, H. Nobach, C. Tropea. 2002, Optical limits of particle concentration for multi-dimensional particle sizing techniques in fluid mechanics. Experiments in Fluids;32, p. 143.
- Pekkarinen, J., Salminen, A., Kujanpää, V., Ilonen, J., Lensu, L., Kälviäinen, H., 2016. Powder cloud behavior in laser cladding using scanning optics. Journal of Laser Applications, 28(3), 032007.
- Thayalan, V., Landers, R.G., 2006, Regulation of Powder Mass Flow Rate in Gravity-Fed Powder Feeder Systems. Journal of Manufacturing Processes. 8, p. 121.
- Yong, Y., 1996. Flow measurement of bulk solids in pneumatic pipelines. Meas. Sci. Technol.7: 16871706.